Multiple Spatial Resolution Image Change Detection for Environmental Management Applications

by

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ABSTRACT

Across boreal forests and resource rich areas, human-induced change is rapidly occurring at various spatial scales. In the past, satellite remote sensing has provided a cost effective, reliable method of monitoring these changes over time and over relatively small areas. Those instruments offering high spatial detail, such as Landsat Thematic Mapper or Enhanced Thematic Mapper (TM or ETM+), typically have small swath widths and long repeat times that result in compositing intervals that are too large to resolve accurate time scales for many of these changes. Obtaining multiple scenes and producing maps over very large, forested areas is further restricted by high processing costs and the small window of acquisition opportunity. Coarse spatial resolution instruments – such as the Moderate Resolution Imaging Spectroradiometer (MODIS) or the Advanced Very High Resolution Radiometer (AVHRR) – typically have short revisit times (days rather than weeks), large swath widths (hundreds of kilometres), and in some cases, hyperspectral resolutions, making them prime candidates for multiple-scale change detection research initiatives.

In this thesis, the effectiveness of 250m spatial resolution MODIS data for the purpose of updating existing large-area, 30m spatial resolution Landsat TM land cover map product is tested. A land cover polygon layer was derived by segmentation of Landsat TM data using eCognition 4.0. This polygon layer was used to create a polygon-based MODIS NDVI time series consisting of imagery acquired in 2000, 2001, 2002, 2003, 2004 and 2005. These MODIS images were then differenced to produce six multiple-scale layers of change. Accuracy assessment, based on available GIS data in a subregion of the larger map area, showed an overall accuracy as high as 59% with the largest error associated with change omission (0.51). The Cramer's V correlation coefficient (0.38) was calculated using the GIS data. This was compared to the results of an index-based Landsat change detection, with C=0.56 and Cramer's V=0.67. This thesis research showed that areas >15 hectares are adequately represented (approximately 75% accuracy) with the MODIS-based change detection technique. The

resulting change information offers potential to identify areas that have been burned or extensively logged, and provides general information on those areas that have experienced greater change and are likely suitable for analysis with higher spatial resolution data.

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LIST OF ABBREVIATIONS

AVHRR	Advanced Very High Resolution Radiometer
DEM	Digital Elevation Model
DN	Digital Number
EOS	Earth Observation Satellite
EOSD	Earth Observation for Sustainable Development
EROS	Earth Resource Observation Science
EVI	Enhanced Vegetation Index
EWDI	Enhanced Wetness Vegetation Index
FMF	Foothills Model Forest
GBRP	Grizzly Bear Research Program
GIS	Geographic Information System
GRS80	Geodetic Reference System
IGBP	International Geosphere Biosphere Programme
ETM+	Landsat 7 Enhanced Thematic Mapper Plus
TM	Landsat 5 Thematic Mapper
MODIS	Moderate Resolution Imaging Spectroradiometer
MRT	MODIS Reprojection Tool
NAD83	North American Datum 1983
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NIR	Near infrared reflectance
NOAA	National Oceanic and Atmospheric Administration
PCA	Principle Component Analysis
SPOT	Systeme pour l'Observation de la Terre
RMSE	Root Mean Square Error
TIROS	Television and InfraRed Observation Satellite
TOA	Top of Atmosphere
UTM	Universal Transverse Mercator
VI	Vegetation Index

1.0 INTRODUCTION

In forests, change occurs at every spatial and temporal scale by natural and human-caused activities. Despite the short-term, economic benefits of natural resource extraction, some of these human-caused activities have potential to significantly alter ecosystems. For example, loss of habitat and increased landscape fragmentation has been shown to result from oil and gas exploration and forest extraction activities (Linke *et al.,* 2006); these changes may threaten the livelihood of vulnerable wildlife species. This is the current situation faced by managers in west central Alberta, specifically along the eastern slopes of the Rocky Mountains, home to a wide variety of sensitive flora and fauna, including the grizzly bear (*Ursus arctos* L.) (McDermid, 2005). With resource extraction activities expanding deeper into environmentally sensitive areas, public interest in the health and status of these ecosystems – and individual species that may be at risk, such as the grizzly bear – can also generate pressure for more sustainable management practices. Developing and implementing these practices is an immense challenge as many of these changes occur on scales that are vast and remote and therefore require resource managers to constantly seek innovative tools.

Satellite sensor remotely sensed imagery has been successfully used in the past to detect, monitor, and display changes over large areas (Gong & Xu, 2003). This information can then be used to develop relationships between biophysical activities (such as grizzly bear movements and resource selection) and anthropogenic changes. Satellite remotely sensed data offers several additional advantages over conventional data sources, such as aerial photography or field methods, because it provides the capability to (Franklin, 2001; Jensen, 2005):

- include extensive geographic regions in their entirety;
- evaluate dynamic landscape patterns (synoptic);
- observe changes and trends across large-scale patterns through time;
- provide spatially and temporally comprehensive data;
- be objective, repeatable, and consistent.

Proper use of the information developed from satellite remote sensing can help managers link science and management by understanding the natural processes impacted as a result of the disturbances (Wulder & Franklin, 2003). An example is the Foothills Model Forest (FMF) Grizzly Bear Research Project (GBRP), initiated in 1999 in west-central Alberta to investigate grizzly bear management issues concerning bear responses and health to anthropogenic changes and their impacts on habitat (Stenhouse & Munro, 2003, Stenhouse & Graham, 2005). Originally, a core study area of roughly 10,000 square kilometers in 1999 was mapped; this has since expanded to over 300,000 square kilometers that, by the end of 2007, will encompass all of the eastern slopes of the

Rocky Mountains from the Montana border to the provincial boundary of the Northwest Territories.

One aspect of the Foothills Model Forest Grizzly Bear Research Project involves mapping the entire bear habitat area to a consistent land cover base *circa* 2005 using a variety of satellite and field data sources. Currently, a land cover map has been assembled based primarily on a collection of imagery consisting of the 'best available' archived Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery (Franklin *et al.,* 2002). These images are segmented using eCognition 4.0, a commercial software package based on object-oriented principles (see Chubey *et al.,* 2006), and then classified into a set of land cover classes considered valuable in grizzly bear habitat analysis (Franklin *et al.,* 2001).

Two main developments suggest that a new approach to update this map product is required:

1) The study area expanded in subsequent years to now include the entire grizzly bear habitat of Alberta (**Figure 1.1**), an area that is much too large to cover with Landsat or similar high spatial resolution imagery on an annual basis, and
2) The malfunctioning of the EROS satellite reduced the availability of Landsat ETM+ sensor data.

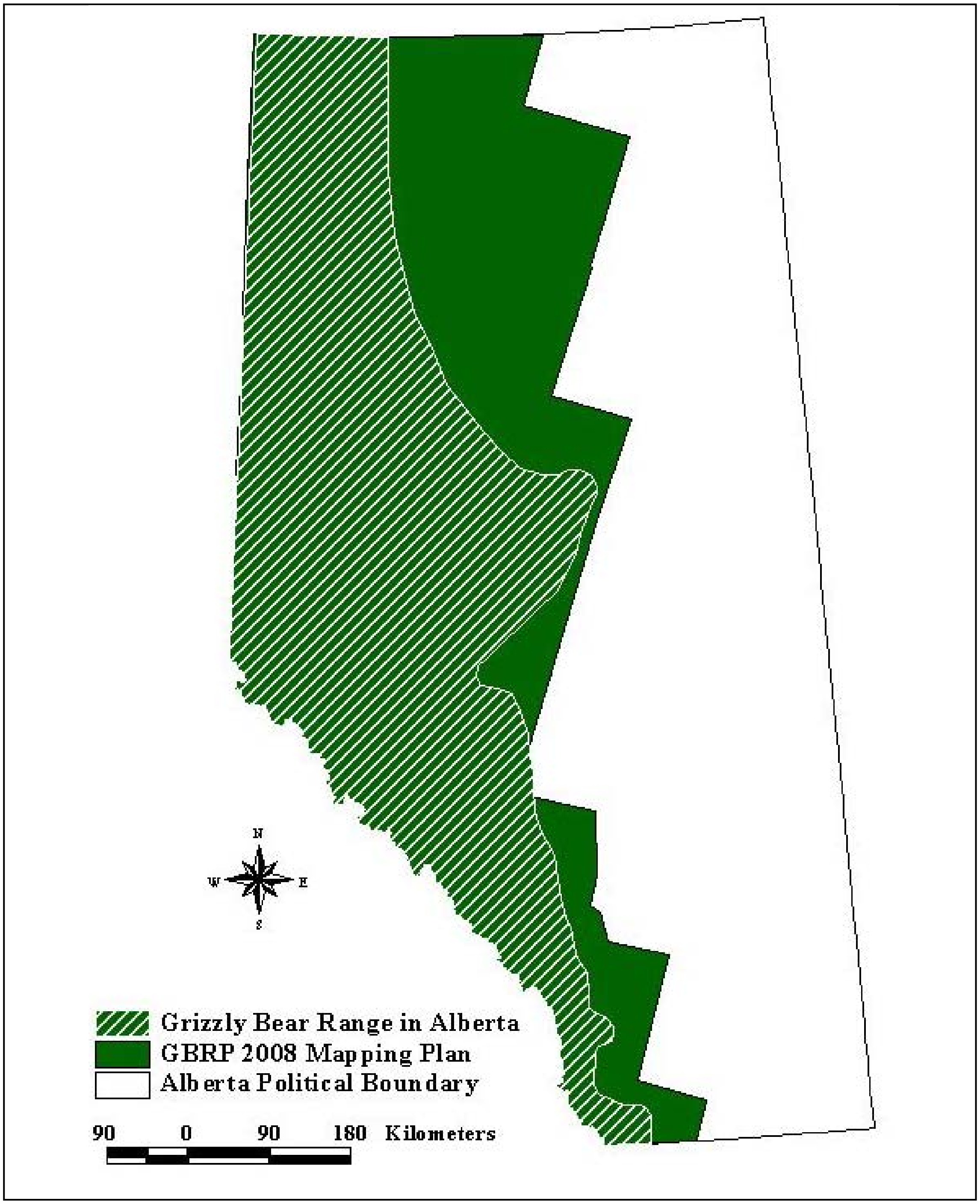

Figure 1.1: Grizzly Bear Range and land cover mapping area in Alberta, Canada

Additionally, acquisition costs, image availability and processing effort associated with creating a seamless, multi-scene, multi-temporal, high spatial resolution, Landsat TM or ETM+ image database suggests that map update procedures should be reconsidered; what is needed now is a standardized method of creating updates for the original land cover map products (Wulder *et al.,* 2003; McDermid *et al.,* 2005). The requirement for up-to-date large-scale, multi-scene landcover maps and research into alternatives for these products is one of the discipline's greatest challenges (Franklin & Wulder, 2002; Coppin *et al.,* 2004; Fraser, 2005; McDermid, 2005).

This thesis research is designed to examine the change detection capabilities and limitations of the relatively-coarse spatial resolution dataset available through the Moderate Resolution Imaging Spectroradiometer (MODIS). Specifically, this thesis determines the power of the MODIS sensor to detect change across areas of grizzly bear habitat mapped using the Landsat TM and ETM+ data with the well-established land cover segmentation and classification approach in Alberta (see Franklin *et al.,* 2001, 2002; McDermid 2005; Chubey *et al.,* 2006; Linke *et al.,* 2006). The resultant MODIS-layer of change in a test area is compared to that produced from the available Geographical Information Systems (GIS)-data layers and aerial photography (GIS-based maps of change), and also to a layer produced using available Landsat TM and ETM+ data. These comparison are then interpreted to indicate the sensitivity and feasibility of applying relatively-coarse spatial-resolution MODIS data to existing Landsat-derived land cover maps; a final analysis suggests the validity of the different change layers in an application of the existing map products to determine the change in landscape fragmentation over the test area.

1.1 Research Questions and Objectives

This thesis research is part of the Foothills Model Forest (FMF) Grizzly Bear Research Project (GBRP) based in the eastern Rocky Mountain slopes of Alberta, Canada. This multidisciplinary research effort was initiated in 1999 to investigate grizzly bear management issues concerning bear response to changing habitat conditions (Stenhouse & Munro, 2003; Stenhouse & Graham, 2005). The project is currently in the seventh year of an 11 year research plan and is focused on relating management issues and questions regarding grizzly bear habitat and health to human use. The larger project is subdivided into five research theme areas including:

i) mapping grizzly bear habitat,
ii) quantifying habitat and landscape structure,
iii) quantifying change in landscape structure,
iv) determining grizzly bear habitat suitability and potential, and lastly,
v) validating and verifying results (Stenhouse & Munro, 2003).

The main thesis research question fits well into the framework outlined above as a successfully updated land cover map will be applied to each of the five theme areas: The main thesis question is: *What is the best way to annually update the existing land cover and habitat map products?* This thesis quantifies and compares the information content of GIS-based data, Landsat and MODIS imagery in order to address the issue of change detection over large areas and long time periods in grizzly bear habitat monitoring applications. Specifically, this research will proceed by answering the following questions:

1. Can MODIS data be utilized to detect accurately anthropogenic change, such as forest harvesting and other disturbances (e.g., caused by seismic exploration and oil and gas development) in different forest ecosystems mapped as grizzly bear habitat using Landsat TM and ETM+ data?
2. Can the updated large-area mapping products be used in applications necessary for use in sustainable environmental management (e.g., landscape fragmentation analysis)?

Specific thesis objectives to be addressed include:

- Determine the method(s) by which coarse resolution MODIS satellite imagery can be used to accurately detect anthropogenic changes across the study area;
- Quantify the map accuracy and sensitivity of the MODIS sensor data analysis compared to the available GIS data set, and a typical Landsat TM or ETM+ sensor-based approach to detect changes within the study area.
- Establish the steps required to create large-area land cover and habitat map update products from MODIS data.

Overall, the main questions of this research thesis are – 1) what method(s) are best suited to detect change in MODIS 250m spatial resolution data, and 2) will the detected change be effective for use in updating large-area map products for environmental management? These are questions that address gaps that exist within the literature and in the practical field of environmental mapping applications.

1.2 Organization of Thesis

This thesis has been organized into four chapters. The first chapter provides background and rationale for the research and introduces the research questions. Chapter two provides a literature review and outlines the existing research concerning relevant change detection techniques; also summarized are the characteristics of Landsat and MODIS sensors included for the thesis research, and a broad rationale on the overall research study. Also included is a description of the challenges associated with large-area land cover mapping and update procedure with any satellite remote sensing data set.

The analysis and research findings are compiled in manuscript form in chapter three, which is entitled: "MODIS-based Change Detection for Grizzly Bear Habitat Mapping in Alberta". This manuscript has been submitted to the journal Photogrammetric Engineering and Remote Sensing for review and publication. Chapter 3 is based on the fact that there are few effective methods available for updating large-area land cover mapping products, especially now that Landsat data are less readily available – certainly not on an annual basis. Testing the sensitivity of the MODIS sensor for this purpose is an important methodological contribution to remote sensing science. Additionally, the multiple-scale, polygon-based technique provides another methodological contribution; this approach has not been tested to date.

Chapter 4 is the final chapter in the thesis; here the focus is on the application of the MODIS change layer to large-area mapping updates for the study region; the issue of landscape fragmentation is used to highlight the differences in Landsat-based, MODIS-based and GIS-based change layers. Also discussed are the challenges, limitations, and areas of future research. A flow chart of tasks is included to outline the focus and direction of this research (**Figure 1.2**).

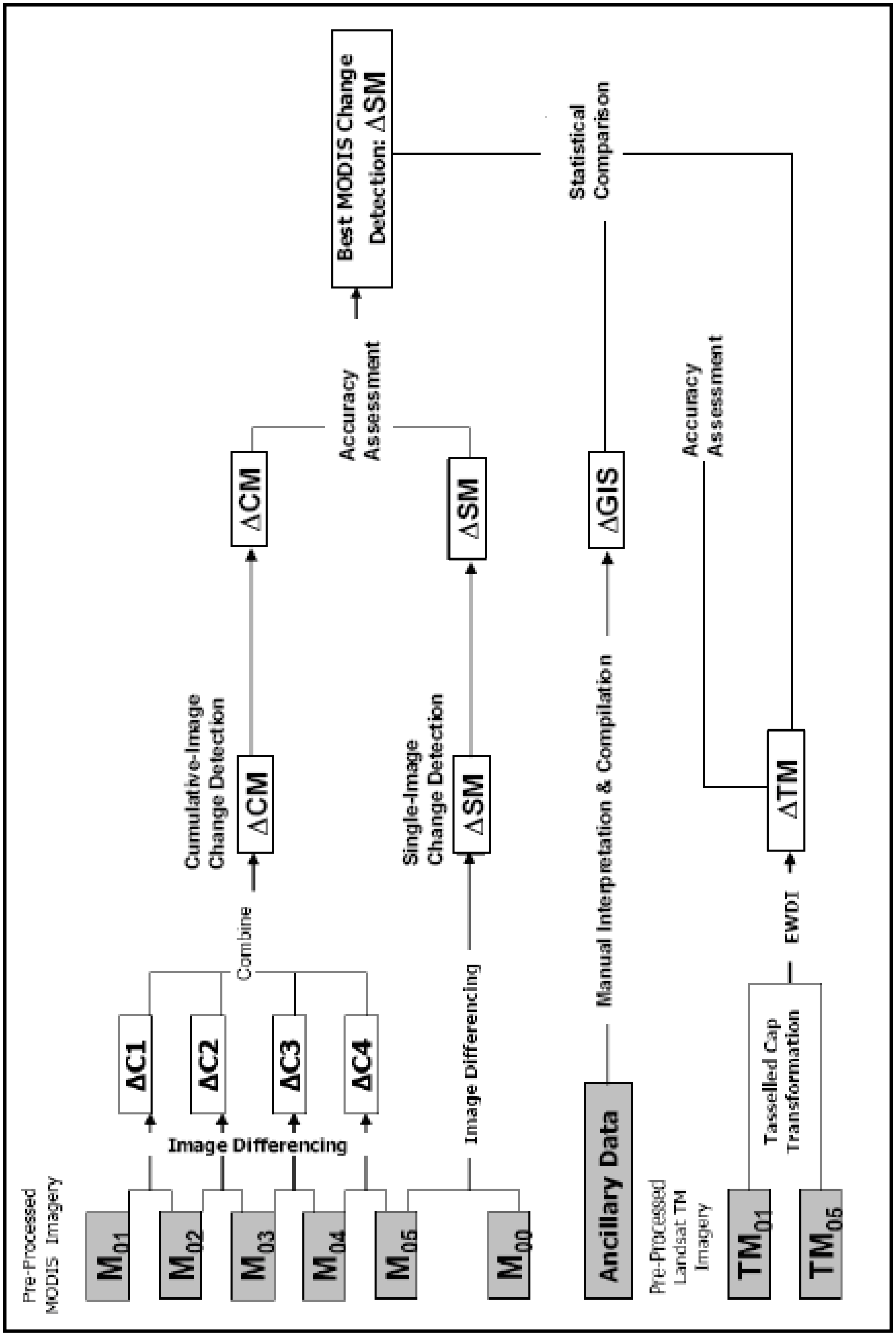

Figure 1.2: Conceptual Framework of the Change Detection Process

2.0 LITERATURE REVIEW

2.1 Change Detection

Change occurs in forest ecosystems through natural cycles and processes within forests and through the activities of humans. Some types of change can occur rapidly and are transformative, including forest harvesting (e.g., clear cuts); others take many years to occur, and are gradual, such as normal forest growth (Gong and Xu, 2003; Jensen, 2005). Recently, there has been an increasing concern regarding the health of the environment in relation to the rate at which resource extraction activities occur. This changing, dynamic relationship of the environment and land use may permanently alter the environment (in a potentially negative manner) and therefore, requires intensive monitoring over time (Lunetta, 1998; Yuan *et al.,* 1998; Franklin, 2001). One of the key elements involved in the global monitoring of environmental change is the accurate, reliable mapping, and quantifying, of physical changes – such as land cover – across small-and-large scale natural environments.

Remotely sensed data are very useful in mapping land cover change; it has been shown many times in the literature and in practical mapping applications that spectral response of pixels acquired by different sensors over time can differ significantly for the same area if the land cover of that pixel has changed (**Figure 2.1**) (Singh, 1989; Jensen *et al.,* 1997). The process of determining that differences are significant has become known as ‘change detection’. The information derived from remote sensing change detection may provide a better understanding of the biophysical relationships in an ecosystem, than is possible with field data alone. With this understanding, managers can use remote sensing as a tool for sustainable environmental management (Jensen, 2000; Mas, 1999; Rogan *et al.,* 2002).

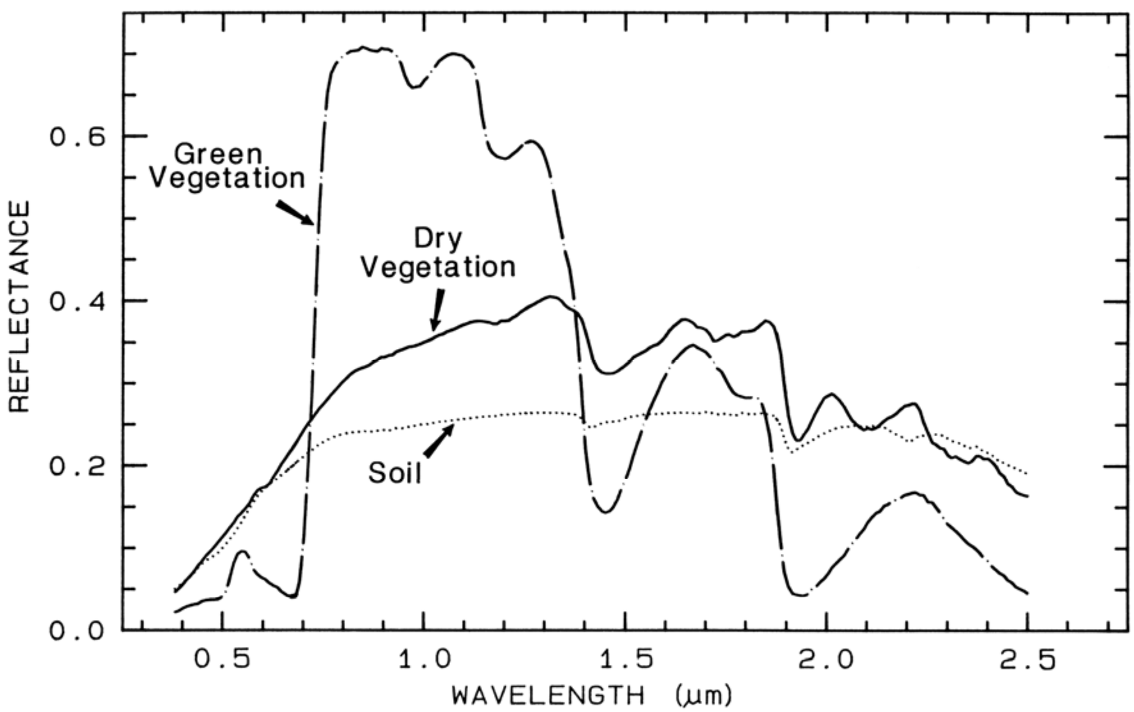

Figure 2.1: Spectral response curve for soils, green vegetation and dry vegetation (Jensen, 2005)

In order to obtain optimal results and achieve the most effective change detection, specific spatial, temporal, spectral and radiometric data issues must be understood for all change detection methods. A typical list, for example, according to Jensen *et al.,* (1997), Lunetta & Elvidge (1998), Coppin *et al.,* (2004), and Millward *et al.,* (2005), would include the following issues:

1) The sensors should have similar precision and be comparable – ideally, the data will be from the same sensor, thereby minimizing sensor radiometric band differencing and issues relating to spatial resolution, and reducing the need for extensive image calibration;

2) The imagery should be from the same time of year or season, for each date, to account for solar illumination angle effects and to minimize differences in seasonal vegetation cover;

3) Images should be co-registered or orthorectified to better than one half pixel accuracy, or 0.5 RMSE (Root Mean Square Error), to minimize spatial offset and distortion effects associated with the geometric registration method used; and

4) Radiometric normalization may be necessary to remove atmospheric effects – differences caused by scattering and absorption by atmospheric constituents, and by differing solar zenith angles, can falsely mimic change in land cover types, these might include cloud and cloud shadow problems (Coppin *et al.,* 2004).

Each of these sources of variability can contribute to an overall commonality between images, enabling analysis at the lowest possible "common denomination" between datasets (Coppin & Bauer, 1996; Lunetta & Elvidge, 1998; Jensen, 2005).

There have been many research studies performed to develop methods and algorithms for obtaining digital change information using a wide variety of remotely sensed data. These are summarized in detail by Singh (1989), Coppin & Bauer (1996), Lunetta & Elvidge, (1998), Yuan *et al.,* (1998), and Coppin *et al.,* (2004) and a few are outlined in **Table 2.1**. Of those reviewed, linear transformations and image differencing are generally reported to perform better than other bi-temporal change detection techniques and are further discussed below.

Table 2.1 Summary of Change Detection Techniques as outlined in Singh (1989), Coppin and Bauer (1996), Lunetta and Elvidge (1998), Yuan *et al*. (1998) and Coppin *et al*. (2004).

Technique	Methodology	Challenges	Benefits
Post-classification Comparison	- Independently produce spectral classification -compare multi temporal classifications pixel-by-pixel	- Results dependent on accuracy of original classification	- No radiometric processing required - No post change classification required
Composite Analysis	- Statistical difference determined using multistage decision logic,	- Very complex especially for multiple dates - Demands prior knowledge of logical interrelationships of the classes - Difficulty in class labelling	- Necessitates only a single classification
Univariate image Differencing	-Subtraction of multi temporal imagery, original or transformed data	- Requires precise registration - highly dependent on change/no change thresholding technique	- Widely adopted Simple
Image Ratioing	- Pixels ratioed, no change ratio=1	-Criticized as being statistically invalid (Riordan, 1981)	- Simple
Bi-Temporal Linear Data Transformation	- Applied to two-date imagery to produce uncorrelated data - Most important is PCA, Tasselled Cap (Crist and Cicone, 1984), and recently MAD (Nielsen *et al.,* 2001)	- PCA requires comprehensive knowledge of study area	- Simple - Very effective
Change Vector Analysis	- Multivariate change detection that processes the full dimensionality of the image data - Produce two outputs: change magnitude and change direction	- Requires perfect registration - Intensive user interaction	- Analyzed change concurrently in all data layers - Highly effective

Technique	**Methodology**	**Challenges**	**Benefits**
Image Regression	- Mathematical model that describes the fit between through step-wise regression - Assumes a linear relationship between multitemporal no change data	- Threshold definition critical - Report accuracies similar to univariate image differencing but more complex	- Regression techniques also account for atmospheric conditional and sun angle
Multitemporal Spectral Mixture Analysis (MSMA)	- Based on differences in high spectral resolution end member	- Requires high spectral resolution imagery	- Provide physically-based, standardized measures of fractional abundance - detect very fine detailed change (i.e. thinning of forests)

2.1.1 Image Differencing Change Detection

Image differencing may be the most commonly used technique to find changed areas in two or more images of the same area acquired at different times (Coppin & Bauer, 1996; Lunetta & Elvidge, 1998; Coppin *et al.,* 2004). Typically, the method subtracts the pixel values in the multi-temporal, co-registered, normalized, original or transformed images. This results in a dataset of positive and negative-value pixels representing 'change', and zero (or near-zero) values that represent 'no change' (Singh, 1989; Coppin & Bauer, 1996; Yuan *et al.,* 1998, Coppin *et al.,* 2004). The original pixel values can be used in the differencing procedure, or possibly image transformations - such as vegetation indices – are first calculated and then subtracted. These indices have usually been found to provide better results than the original pixel values in image differencing; for example, Coppin *et al.,* (2004) suggested that indices are more strongly related to changes in the scene rather than changes in single bands because they are more 'physically-based'. Of the many potential examples of such 'physically-based indices', three are cited here to illustrate the power of the index-based differencing change detection approach:

1) Nelson (1983) detected forest canopy changes in northeastern deciduous forests caused by gypsy moth defoliation better with a red/infrared vegetation index calculated from Landsat data than any single band difference or original band ratio; the logic suggested was that the defoliation caused an 'opposite' change in the two bands, which therefore could be 'enhanced' with the simple ratio index;

2) Lyon *et al.,* (1998) found that the Landsat-based Normalized Difference Vegetation Index (NDVI) was useful for detecting and monitoring vegetation change and deforestation in the Amazon; here the changes from forest cover to agriculture crop species and exposed soil was obvious as these cover types displayed spectral responses that were quite different in the red and near infrared bands; and,

3) Franklin *et al.,* (2002) found that the Enhanced Wetness Difference Index (EWDI), which is based on a transformation of the six reflective TM or ETM+ bands, was very effective in detecting forest change in a mixed-forest region of New Brunswick, Canada; they suggested that the use of the middle-infrared bands – which were more sensitive to moisture content – in the index would outperform an index based on only the red and infrared bands.

These three examples suggest the range and diversity of change detection applications that are possible with a physically-based index-based difference approach, in which two images acquired at different times are compared (i.e., subtracted) to reveal significant differences in land cover or other physical characteristic (e.g., forest canopy defoliation). A key feature of this approach is to understand the way in which changes on the ground can influence the resulting spectral response as measured by the satellite sensors in different bands (i.e., the gypsy moth defoliation caused an increase in near infrared response, and a decrease in red response, which when ratioed, enhanced the differences).

As these many studies and others suggest, there are numerous options that must be considered when selecting a change detection technique. Each of the methods above can be used alone or in conjunction with others. Assessing the needs of the user, the complexity of the landscape, the variability of the spatial patterns and the existing literature will help determine the best technique. These issues are especially pertinent for applications of high spatial resolution imagery, for example, the data acquired by the SPOT and Landsat sensor systems. However, within the literature reviewed for this thesis, it is quite clear that very few studies have focussed on determining the best methods applicable to large, regional areas (those exceeding 10,000 square kilometres, covering many individual Landsat or SPOT scenes); even fewer have tested the applicability of relatively-coarse resolution imagery, such as MODIS or AVHRR, for the purpose of updating large-area land cover maps produced from higher spatial resolution sensors such as Landsat TM or ETM+. The available coarser resolution change detection studies are reviewed in the following section.

2.2 Coarse Resolution Change Detection

Increasing interest in regional and global mapping projects has generated a trend towards coarse spatial resolution change detection studies, including MODIS (Coppin *et al.,* 2004; Fraser *et al.,* 2005). Usually, the interest is in updating similar 'global' data products, such as those produced by classifying AVHRR data into broad land cover classes covering continental or regional areas – as mentioned in the previous section, few studies have reported on the use of these coarser spatial resolution data to update a Landsat-based map product. Although high spatial detail is always reduced in these applications, there are some interesting advantages associated with using this type of coarser-resolution imagery. For example, fewer scenes are required to cover vast areas, the short revisit time provides a large selection of available imagery across all seasons, and much of this coarse resolution satellite data are freely available. Despite these benefits, the low spatial detail cannot be expected to provide the same information content as the higher spatial resolution sensors, and for many management studies however, this restricts the use of the coarser resolution data sets to only playing a supplemental role or possibly to identify areas of change for which higher spatial detail imagery must be acquired (e.g., an airborne mission).

Coarse resolution change detection studies have proven successful when the change features of interest are large and cover regional areas; studies have been reported ranging from climate-driven phenology (Moody & Johnson, 2001) to natural disturbances (Tansey *et al.,* 2004; Chuvieco *et al.,* 2005) to forest harvesting (Zhan, *et al.,* 2002). Recent attempts use an assortment of change detection techniques that include change metrics (Fraser *et al.,* 2005), iterative estimation (Le Hegarat-Mascle *et al.,* 2005), end member and spectral signatures (Thenkabail *et al.,* 2005) logistic regression (Fraser *et al.,* 2003), and decision trees (Zhan *et al.,* 2002). Multi-date image differencing has been used in the past (Kasischke & French, 1995), and recently an object-based classification for burned areas was performed on coarse spatial resolution data by Gitas, *et al.,* (2004). Most of these studies focus on NOAA’s Advanced Very High Resolution Radiometer (AVHRR) archive data. More recently, the Moderate

Resolution Imaging Spectroradiometer (MODIS) has been used in change detection; these studies are reviewed in the following section.

2.3 The Moderate Resolution Imaging Spectroradiometer (MODIS)

The Moderate Resolution Imaging Spectroradiometer (MODIS) instrument, is a coarse resolution scanning radiometer onboard the Terra (EOS AM) satellite launched December 18, 1999 to replace the Advanced Very High Resolution Radiometer (AVHRR) on the earlier NOAA (National Oceanic and Atmospheric Administration) and TIROS (Television and InfraRed Observation Satellite) satellite platforms. With a temporal resolution of one or two days, the MODIS sensor has been acquiring usable data since February 24, 2000 across 36 spectral bands with spatial resolutions varying from 250 meters to 1000 meters across the entire globe (Zhan *et al.,* 2002). The first seven bands available from the MODIS instrument are designed for land surface remote sensing (King *et al*., 2004). The data are preprocessed by a team of leading scientists to produce high quality, cloud free mosaics available in 16 day intervals (McDermid, 2005). Also created are a series of 44 high-end data products within 5 categories: calibration products, atmospheric products, oceanic products, cryospheric products and land products. These are available at no charge from NASA's EOS Data Gateway and provide valuable research tools for the remote sensing community (King *et al*., 2004). Three specific products are of particular interest and are described in the following sections: MOD12C1 Land Cover Classfication, MOD44 Vegetation Cover Conversion (VCC), and MOD13Q1 Vegetation Index (VI).

2.3.1 MODIS Data Products: MOD12C1 Land Cover Classification

The Land Cover Classification product, MOD12C1 identifies 17 vegetated and non-vegetated land cover classes (**Table 2.2**). Available at 1km resolution, these classes are based on the International Geosphere Biosphere Programme (IGBP) global vegetation classification scheme (Justice *et al.,* 2002). The classification is performed using a supervised decision tree classification method consisting of a minimum of 1500 training sites. Unfortunately, the MOD12C1 product is only current to 2003 and therefore not applicable for updating existing maps beyond that date (King *et al*., 2004). Eventually, however, testing MOD12C1 map accuracy and precision for the purpose of change detection using the multi-date post classification comparison technique may prove to be a successful research initiative.

2.3.2 MODIS Data Products: MOD44 Vegetation Cover Conversion (VCC)

The Vegetation Cover Conversion (VCC), MOD44 product provides 250m resolution forest change - from closed canopy forest (>60% treed) cover to non-forest (<40% treed) - on a quarterly basis (King *et al*., 2004). Essentially, this is a land cover classification update (Huete *et al.,* 1999; Justice *et al.,* 2002), unfortunately, is limited to the humid tropical regions of the globe (20 deg N latitude to 20 deg S. latitude). Therefore this product is not applicable to many studies, including the present thesis research study area. An interesting idea, beyond the scope of the present thesis, might involve simulating this data product in temperate regions.

Table 2.2 Landcover classes available from the MOD12C1 product

Majority Land Cover Type 1	Index	Color
Water	0	
evergreen needleleaf forests	1	
evergreen broadleaf forests	2	
deciduous needleleaf forests	3	
deciduous broadleaf forests	4	
mixed forests	5	
closed shrublands	6	
open shrublands	7	
woody savannas	8	
savannas	9	
grasslands	10	
permanent wetlands	11	
croplands	12	
urban and built-up	13	
cropland/natural vegetation mosaic	14	
snow and ice	15	
barren or sparsely vegetated	16	
unclassified	254	

2.3.3 MODIS Data Products: MOD13Q1 Vegetation Index

The EOS Data Gateway also offers the MOD13Q1 Vegetation Index data product, and several authors have strongly suggested that the use of the MOD13Q1 for change detection may prove successful (e.g., Chuvieco *et al.,* 2005). All of these MODIS products are considered experimental by NASA, and further research into their scientific validity is currently underway. Nevertheless, they have shown two important aspects of change detection using coarse resolution imagery: 1) many human-induced land cover changes are vast and occur at coarse spatial scales; and 2) these landscape changes are possibly captured in general data products based on coarse resolution sensor data such as those obtained by MODIS (Justice *et al*., 2002; Zhan *et al.,* 2002).

More details on the different approaches that can be considered is provided in the following sections; specifically, details on the different indices, the comparison with the higher spatial resolution imagery such as Landsat, and the mapping implications are described. The intention is to provide the reader with a firm background in the general area of change detection and vegetation indices before introducing the specific study comparing the MODIS-based change detection with the other data sets in the grizzly bear habitat mapping application.

2.4 Vegetation Indices

Across the spectral range of the MODIS sensors, only two out of the seven bands collected for land surface remote sensing, are available at the 250m resolution: Band 1 – Red: 620-670nm and Band 2 – Near Infrared (NIR): 841-876nm. Research has suggested that these are among the most important spectral regions for remote sensing of vegetation change, and they form the basis of many vegetation indices, some of which have been developed for Landsat-based applications. Some studies (e.g., Franklin *et al.,* 2001) have suggested for forest change that 'transformations' such as the EWDI were superior to straight ratio-based indices – but then, even in that study, an index was created using the transformed bands as input. The indices – regardless of the input variables which could be the original bands or transformed data – do have the ability to enhance vegetative attributes by summarizing pertinent information contained in several bands while simultaneously reducing original data volume for processing and analysis time.

An index can offer an additional advantage over single-band radiometric responses with the ability to relate to changes in spectral values across the entire scene rather than those only detected in specific bands (Coppin *et al.,* 2004; Jensen, 2005). Despite the inability for one data product to completely summarize all information in multidimensional spectra, the index-approach has been established to enable precise spatial and temporal comparisons of remotely sensed data. Studies based on the performance of indices include those by Singh (1989), Coppin & Bauer (1996), Lyon *et* *al.,* (1998), Yuan *et al.,* (1998), Franklin *et al.,* (2001), Wilson and Sader (2002), and Zhan *et al.,* (2002). Many of these studies use a simple index such as the Normalized Difference Vegetation Index (NDVI), which is one of the most popular in remote sensing (and is described in the following section), and is also the basis for one of the algorithms used to create the MOD13Q1 data products.

2.4.1 Normalized Difference Vegetation Index (NDVI)

Probably the most widely adopted vegetation index used for forestry studies is the Normalized Difference Vegetation Index (NDVI) originally developed in the early 1970s (Lyon *et al.,* 1998). The NDVI is based on the well-known relationship between healthy vegetation and reflected energy within the visible Red and Near Infrared (NIR) bands. Colwell (1974) was able to demonstrate that much of the energy in the NIR band is reflected by green vegetation, while the energy in the visible red portion of the electromagnetic spectrum is absorbed for photosynthesis – the dramatic increase from the red to the infrared portion of the spectrum is now more commonly referred to as 'The Red Edge' (**Figure 2.3**). Band ratioing the difference of these values to their sum results in normalized NDVI values that provide a simple, quantitative estimation of the health and density of the vegetation between zero (no vegetation) and one (dense vegetation) (Tucker, 1979; Wilson & Sader, 2002; Jensen, 2005).

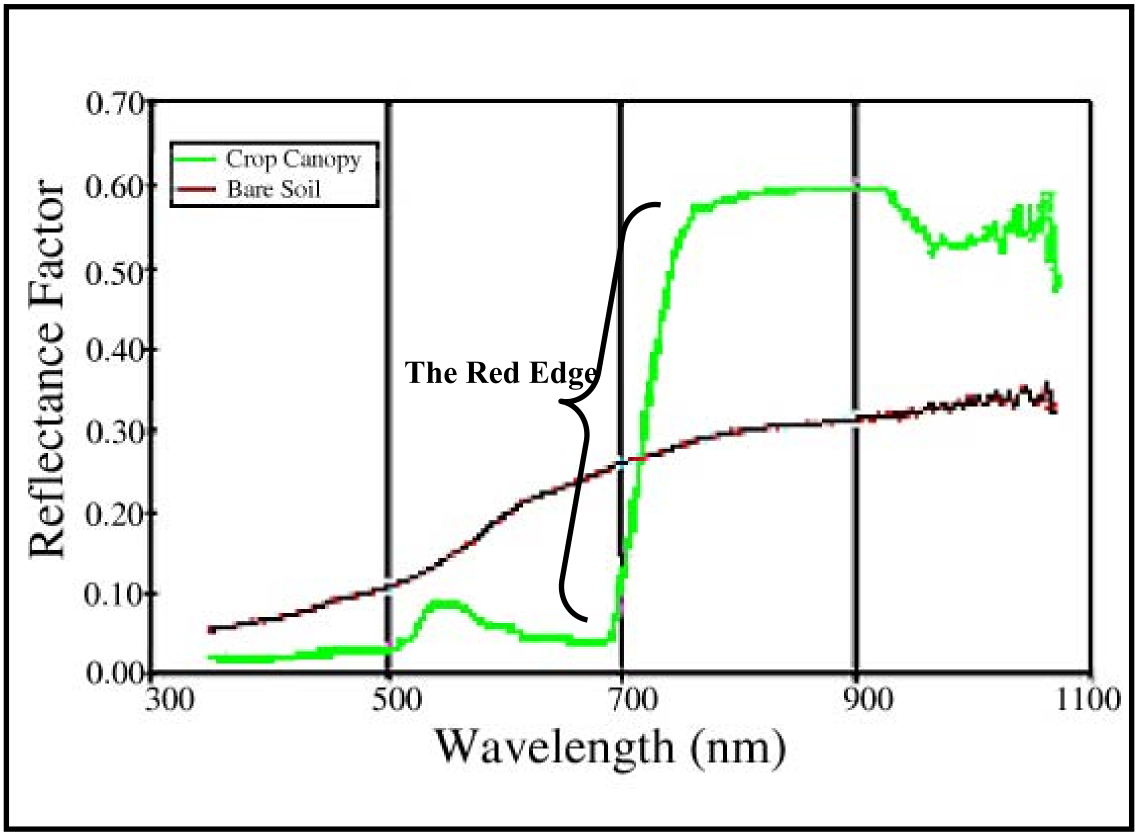

Figure 2.2: The Red Edge
High levels of foliage reflect with high values in the NIR portion of the spectrum and are absorbed in the visible, red portion (Tucker, 1979; Jensen, 2005).

Although very effective, one issue related to using NDVI products is that this relationship peaks and 'saturates' to a level where reflectance values that exceed this point are not distinguished (Jensen, 2005). In other words, while it may be possible to distinguish areas of sparse vegetation from areas of dense vegetation, it becomes more difficult as the amount of vegetation increases – it is therefore not possible to map differences between dense and 'more dense' beyond a certain threshold. Additionally, information contained in other areas of the spectrum may provide useful information for detecting specific changes that may not be evident in this relationship – this was one of the reasons that the EWDI outperformed the NDVI in the study reported by Franklin *et* *al.,* (2002). In another example, Fraser *et al.,* (2003) found that the use of the Short Wave Infrared (SWIR) band significantly improved the results of burned area change detection compared to the NDVI in several vegetative studies across Canada. However, the differences between the application of NDVI and other indices is not always consistent for forest-based studies (there may be a species-effect, for example), and therefore, the NDVI remains one of the most widely adopted approaches for general-purpose applications. Also, virtually all the major sensor systems have both a red and an infrared band, necessary to calculate NDVI, while many do not have the short-wave or mid-IR bands necessary to calculate other indices such as the EWDI.

In light of its popularity and versatility, the EOS Data Gateway has developed MODIS-based NDVI and Enhanced Vegetation Index (EVI) data products. These are available in an up-to-date series, compiled from the beginning of the Terra EOS AM satellite (launched 1999) that provides data coverage for North and South America (Huete *et al.,* 1999). The main difference between the NDVI and the EVI is that distortions from atmospheric influence and canopy background signal sometimes found in the NDVI data product are corrected and removed for the EVI data product (Huete *et al.,* 1999; King *et al*., 2004). The resultant EVI product offers improved sensitivity in high biomass regions and improved vegetation monitoring. Additionally, the EVI does not become saturated as easily as the NDVI when viewing forests and other areas of the Earth with large amounts of chlorophyll (Huete *et al.,* 1999). With the proven success of the NDVI for forestry based change detection studies of higher spatial resolution, and the potential of the EVI to improve on the shortcomings of the NDVI.

2.4.2 Enhanced Wetness Difference Index (EWDI)

The Enhanced Wetness Difference Index (EWDI) is a vegetation index commonly used for generating change/no change information in vegetated areas using Landsat TM or ETM+ data. It is based on one of the most successful Principal Component Analyses developed for Landsat data by Kauth & Thomas (1976) and refined by Crist & Cicone (1984); it is known as the Tasselled Cap Transformation. Originally used for understanding agricultural crop development with early Landsat data (prior to the introduction of the TM sensor in 1984), this transformation has proven useful for other vegetation applications (**Figure 2.3**). For example, Cohen *et al.,* (1995) used it for mapping coniferous forest species, age, and structure in the Pacific Northwest Region; more recently, Franklin *et al.,* (2001) used it to detect forest change in a wide variety of Canadian forest ecosystems.

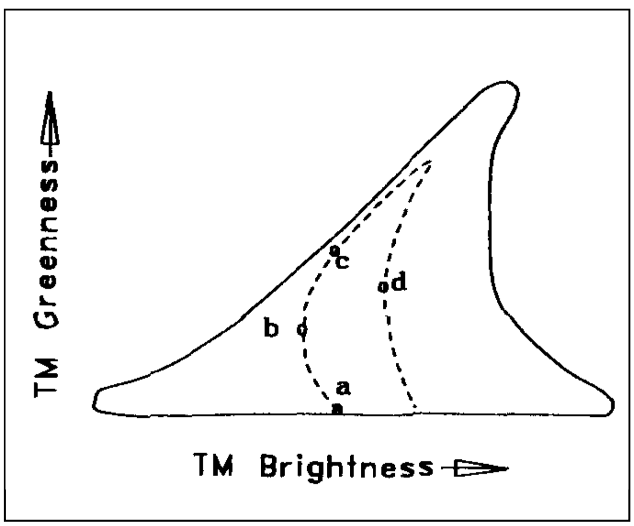

Figure 2.3: Brightness vs Greenness to produce the Tasselled Cap transformation. It is efficient agriculturally because it follows the growing season that starts with bare soil (a) that "greens up" as the crop matures (b) and eventually peaks with the canopy entirely covering the ground (c). At this time, the crop is usually harvested and the tasseled cap drops and stabilizes in to senescence (d) (Kauth and Thomas, 1976).

This transformation is ‘guided’ to produce consistent variables that can more easily be compared between dates and sensors and often used to deduce a physical explanation for changes in surface conditions (Jensen, 2005). It results in three new indices often called brightness, greenness and wetness (or yellowness with the earlier Landsat data sets). Brightness is typically related to overall reflectance, and greenness is used as a measure of the green vegetation present; wetness, on the other hand, may be related to moisture content, and has been used as a ‘maturity index’ to quantify forest vegetation (Jensen, 2005; Franklin, 2001).

For this specific change detection method, the wetness index derived from the PCA tasselled cap transformation is used to produce a consistent ‘wetness’ variable that can be compared between dates (Fung & LeDrew, 1987; Franklin et al., 2001; Millward et al., 2005). Second, the EWDI is normalized in the same way as the NDVI – by dividing the difference by the sum of the two dates. As a method of deducing a physical explanation for changes in forest conditions, it is considered to be one of the best approaches for time-series analyses (Jensen, 2005; Yuan *et al.,* 1998; Franklin, 2001). The normalization process is preferred as it reduces the influence of atmospheric conditions (Franklin, 2001).

Both vegetation indices were evaluated for this research however preliminary results suggested that the NDVI product outperformed the EVI product for this application. Upon this finding, a decision was made to exclude the EVI from the evaluation in order to stay within the scope of this research. One possible explanation is that because the EVI product combines bands with differing spatial resolutions (250m and 500m) and the NDVI uses only those available at 250m spatial resolution, additional preprocessing of the EVI data is required for best results.

2.5 Landsat Thematic Mapper

The Landsat 5 Thematic Mapper (TM) and the Landsat 7 Enhanced Thematic Mapper Plus (ETM+) are 8-bit, moderate resolution sensors (25-30 meter resolution), both part of NASA's EROS satellite mission. In May 2003, an instrument anomaly was detected onboard the EROS satellite that collects Landsat 7 ETM+ data. With restorative efforts, Landsat 7 ETM+ data are still available for purchase, though the malfunction remains and at least 25% of the information collected after this date are severely distorted. This was a fateful event within the science of remote sensing as significant research efforts have contributed to an extensive literature base focussed on this sensor. Additionally, the features of the sensor make it an optimal tool for resource management, for example: much data availability, long term continuity, and extensive geographic coverage. Further, the spatial resolution of the sensor is fine enough to identify and detect adequate features and changes across the landscape in an economic manner (McDermid *et al*., 2005). For example, all previous mapping efforts within the GBRP and the nation-wide government initiative to map all forests across Canada – known as the Earth Observation for Sustainable Development (EOSD) Program (Wulder *et al.,* 2003) - have relied on Landsat TM and ETM+ imagery for creation of their map products (Franklin *et al.,* 2001; Wulder *et al.,* 2003).

The failure of Landsat 7 ETM+ has forced users to rely on Landsat 5 TM data for most Landsat image requirements. This particular sensor has been in orbit since March 1984, far exceeding its expected six-year lifespan. However, with spatial and radiometric resolution comparable to that of Landsat 7 ETM+, coupled with recent calibration advancements and pre-processing techniques, the overall quality of the data is excellent and the sensor continues to perform adequately (Chander & Markham, 2003). Data availability, however, remains a problem because of the low temporal resolution (revisit cycle of 16 days).

The unpredictable nature of remote sensing instruments as demonstrated by the performance of the Landsat sensors poses the challenge to remote sensing scientists to constantly explore alternatives. This is especially true for large-area projects that require several scenes annually or over several years. For example, methods of updating existing land cover map products must enable users to maintain the status of their products when the original mapping data are no longer available, such as the case with Landsat 7 ETM+. It is important to consider the user requirements and the challenges of these large-area mapping initiatives, such as costs, image availability, processing time, accuracy and usability.

The MODIS sensor offers an excellent option for dealing with many but not all of these mapping criteria. The largest challenge, of course, is the loss of spatial detail compared to Landsat (**Figure 2.4**); clearly, the type of change and land cover that can be mapped with MODIS would be different than those mapped with Landsat ETM+, if those data were available. However, the potential of using the MODIS sensor for image

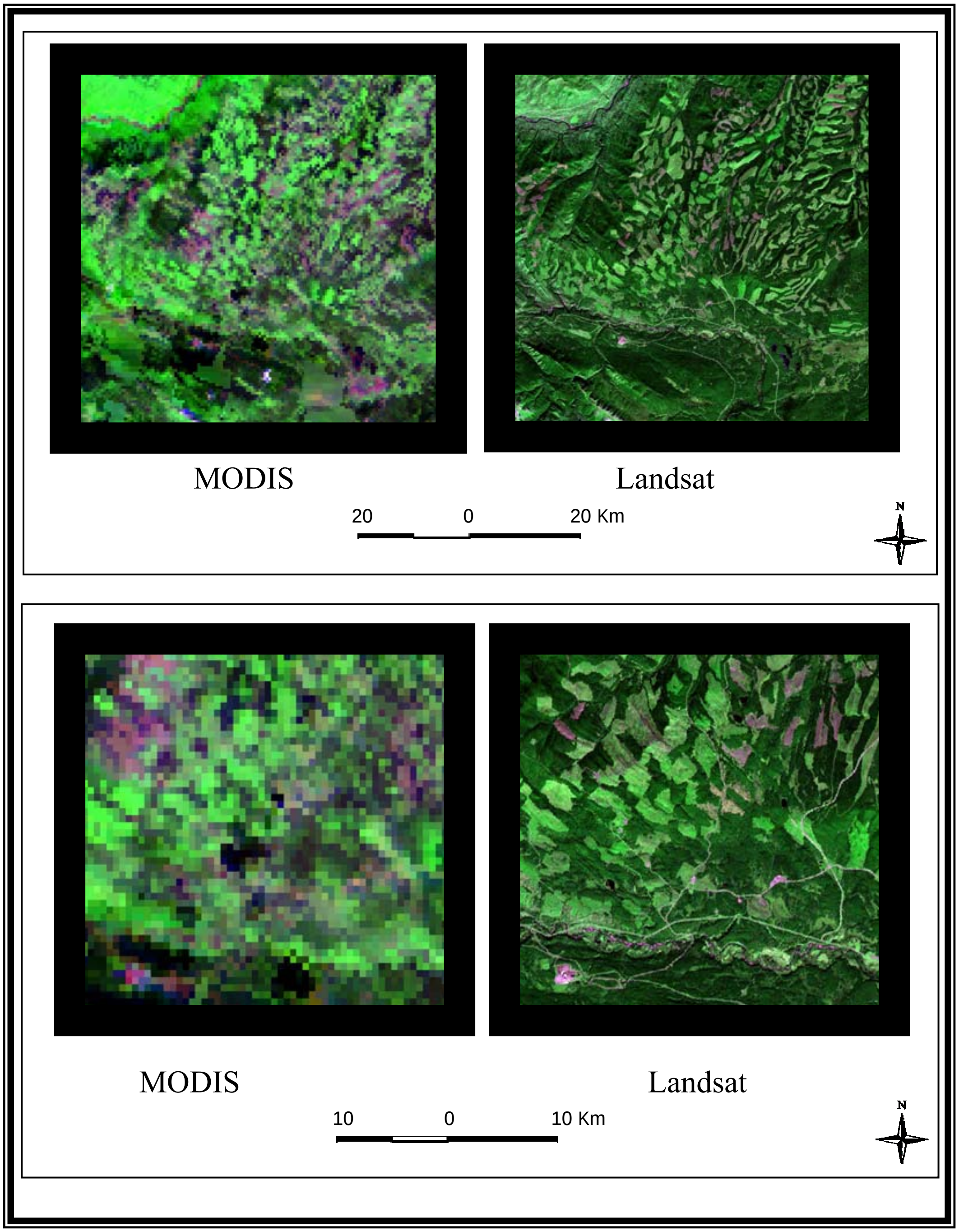

Figure 2.4: Difference in spatial resolution between Landsat 30m data and MODIS 250m data: False color composite (RGB 342) of a forested area subject to intense landuse

differencing for the purpose of producing change updates to a Landsat land cover map has not yet been assessed. It should be possible, incorporating the simple image differencing techniques used with higher spatial resolution data, to provide a comprehensive, large-area map update that, though not as accurate as the Landsat product would be, might still be adequate for successful application results.

Another question that must be addressed when considering the use of MODIS data updates is: *What is the best method of integrating the change layer into the existing land cover map?* Obviously, the 250m MODIS pixel is much larger than the original 30m Landsat pixels used to create the map – therefore, simply merging these larger pixels into the existing map would generate a significant level of 'blockiness' to the original map quality. One emerging area of research within remote sensing, which might help alleviate this concern, is the trend from a pixel-based update to a polygon-based one (Wulder *et al.,* 2006). The new approach offers some advantages over the pixel-based method by working to eliminate the limitations commonly found within traditional pixel-based techniques. Some of these issues are briefly reviewed in the next section.

2.6 Object-Based vs. Pixel-Based

When dealing with a satellite image database, there are copious amounts of information available that are directly related to the spatial resolution of the imagery. Apart from the obvious spectral response patterns associated with each pixel, there exist equally important spatial relationships that are often overlooked with traditional methods. Over the past few years, one of the trends within remote sensing research is towards polygon-based mapping approaches (Wulder *et al.,* 2006). The difference between the pixel-based approach and the polygon-approach is deceptively simple. The polygon method combines a group or a cluster of pixels based on a 'similarity' criterion, instead of focussing on each pixel individually. Each approach has its advantages and disadvantages. The main advantage of using a pixel based technique is that the method has been used extensively for many applications and, therefore, a strong knowledge base exists. Processing is typically fast and relatively easy to convert to a map product that users will understand – the output pixels are mapped in the same configuration as in the original image. However, there are several disadvantages associated with pixel-based methods that have limited the technology for several years.

For example, a per-pixel technique uses only the spectral information from each pixel. In turn, this divides the landscape into an arbitrary grid system that inadequately represents the landscape (Smith and Fuller, 2001). A polygon-based technique can consider more spatial-based characteristics, for example spectral signature, shape, and other neighbour attributes. Secondly, when dealing with per-pixel classifications, pixels or groups of pixels representing one land cover class may not have the same spectral information due to noise, atmospheric conditions, or natural variation of the surface, for example, clouds, sun angle, and topography. These effects can cause the incorrect classification of pixels of the same feature (Smith and Fuller, 2001). Polygon-based methods deal with this limitation by including other spatial features, including size and shape along with the mean spectral values to make a decision. (Smith and Fuller, 2001).

One example of a pixel related challenge is found with the "Regenerating Forest" class used in the land cover map of the Grizzly Bear Research Program. Typically this class consists mainly of clear cuts and burns but the spectral reflectance values of the vegetation found within the class vary significantly across the landscape (ranging from, herbaceous, shrub, barren soil, etc). For this reason, it is difficult to select appropriate spectral-based training data to adequately represent this class in the classifier. Using a polygon method, the "Regenerating Forest" class is first classified based on shape and other spatial characteristics, and further decisions may be based on spectral characteristics

With traditional, pixel-based approaches, the user essentially trains the data by selecting numerous pixels that represent the range in spectral reflectance for each class. The pixel is the phenomenological unit of analysis – the minimum mapping unit, for example. The object-oriented approach, or the polygon-based approach, instead of using pixels as the minimum unit, uses some logical spatial structure to reorganize the basic mapping units. Then, any subsequent processing is designed to reveal changes in these units, not in the individual pixels that were used to create them. Because of the large differences in spatial resolution between the MODIS data and the original map input

(Landsat), a polygon-based change detection might be more appropriate for the final map update.

2.7 Conclusion

This review has summarized some of the main issues associated with change detection using satellite remote sensing imagery; consideration of spatial resolution, data processing (such as vegetation indices), and map output or update procedures are critical to ensure the most effective map products are available to the end users. A significant gap in existing knowledge of change procedures applied over large areas to an existing Landsat land cover map should be addressed – in essence, it is important to be able to identify the capability of coarser-resolution imagery, such as MODIS, in updating land cover maps derived from Landsat sensors. Since Landsat sensor data have reliability problems, and other sensor packages (e.g., SPOT) would be too expensive and difficult to acquire over large areas, a research project to determine the best accuracy and approach to use with MODIS data would be a useful contribution to the grizzly bear mapping project in the Canadian Rockies.

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3.0 MODIS-BASED CHANGE DETECTION FOR GRIZZLY BEAR HABITAT MAPPING IN ALBERTA

A. D. Pape, and S. E. Franklin, Submitted to: Photogrammetric Engineering and Remote Sensing, 1 September 2006

3.1 Abstract

The Rocky Mountain Foothills in Alberta, Canada, are subject to change from anthropogenic activities such as mining, forestry, recreation, and oil and gas exploration, in addition to natural changes including wildfire. The impact of these activities often cover large areas and may have a negative influence on the natural processes of ecosystems and habitats of many different species, including Grizzly Bears (*Ursus arctos* L.), that exist in these areas. In an attempt to ensure forests are managed sustainably, environmental managers are constantly seeking to apply innovative tools, including satellite remote sensing. A remote sensing approach has bees being developed to map land cover and physical variables, and to detect and identify various types of change at a variety of scales across an area from the Montana border north to the Northwest Territories. An issue with mapping such a large geographic area is that the original sensors used to create the land cover maps with adequate spatial detail have small swath widths, long repeat times, and high costs. Additionally, acquisition may be a problem; and processing of the large number of individual scenes requires great effort. For these reasons, interest in available coarser spatial resolution sensors, such as MODIS, for the purpose of updating maps has increased.

In this paper, the effectiveness of using 250m spatial resolution MODIS NDVI data for the purpose of updating an existing large-area, Landsat-based land cover map is tested. We resampled a MODIS NDVI time series (2000-2005) for the purpose of change detection and applied image differencing to create a layer of change at the scale of the original polygons. Accuracy assessments showed an overall accuracy as high as 59% with most of the error associated with change omission (0.51). The Cramer's V statistic (0.38) was calculated against a manual GIS change layer and also compared to that obtained in a small test area using a Landsat-based approach which employed the Enhanced Wetness Difference Index (EWDI). Results for the Landsat approach were better than the MODIS results (Cramer's V=0.67). Three main issues arose in the study including 1) selecting change threshold values, 2) pixel location and 3) the large difference in spatial resolution. Changes in segments or polygons >15 hectares (10,000m^2) were adequately represented with the MODIS technique; this offers potential for identifying burned areas, and large forest harvesting areas. The MODIS change layer also provides general information on areas that may be suitable for analysis with higher spatial resolution data.

3.2 Introduction

Change occurs across all forest ecosystems through natural processes and through the activities of humans. The rate of change can vary from rapid deforestation to the less obvious effects of recreational activities. The rate at which resource extraction activities occur must be monitored over time (Jensen, 2005; Lunetta and Elvidge, 1998; Yuan *et al.,* 1998; Gong & Xu, 2003, Wulder *et al.,* 2003, Fraser *et al.,* 2005). One of the key elements involved in the monitoring of global change is the accurate, reliable mapping, and quantifying of physical changes across these natural environments (Franklin *et al.,* 2002; Franklin & Wulder, 2002). Often these initiatives are conducted over small geographic areas, however, with recent concern regarding diminishing wildlife habitat there is a trend towards regional and global projects (Franklin, 2001; Olsen *et al.,* 2002; Wulder *et al.,* 2003, Stenhouse and Graham, 2005).

The mapping of large areas significantly limits the applicability of traditional field methods suggesting the need to seek alternative methods. Remotely sensed data have proven very useful for the purposes of supporting large-area mapping and monitoring programs. Satellite remote sensing has the ability to consistently deliver a certain quality of information with regular temporal frequency, however, the challenge lies in obtaining map products that are temporally accurate and spatially adequate to meet the users' needs (Gong & Xu, 2003). For example, one goal of the Foothills Model Forest Grizzly Bear Research Program (FMFGBRP) is to map the entire grizzly bear range in Alberta (**Figure 3.1**) using 30m Landsat TM or ETM+ imagery in an effort to determine the relationship between grizzly bear response and health to intensive land use activities (Stenhouse & Graham, 2005). The entire study area encompasses a mosaic of nearly 25 Landsat TM scenes, over 340,000 square kilometers, a product that is essentially impossible to duplicate at the same spatial resolution annually or even bi-annually due to short growing seasons and persistent cloud cover in these areas (Wulder *et al*., 2004; Fraser *et al.,* 2005). As a result, the working maps are often out of date (i.e., based on most recent 'best' available TM or ETM+ data). There is dearth of alternative methods to update these products (McDermid *et al.,* 2005).

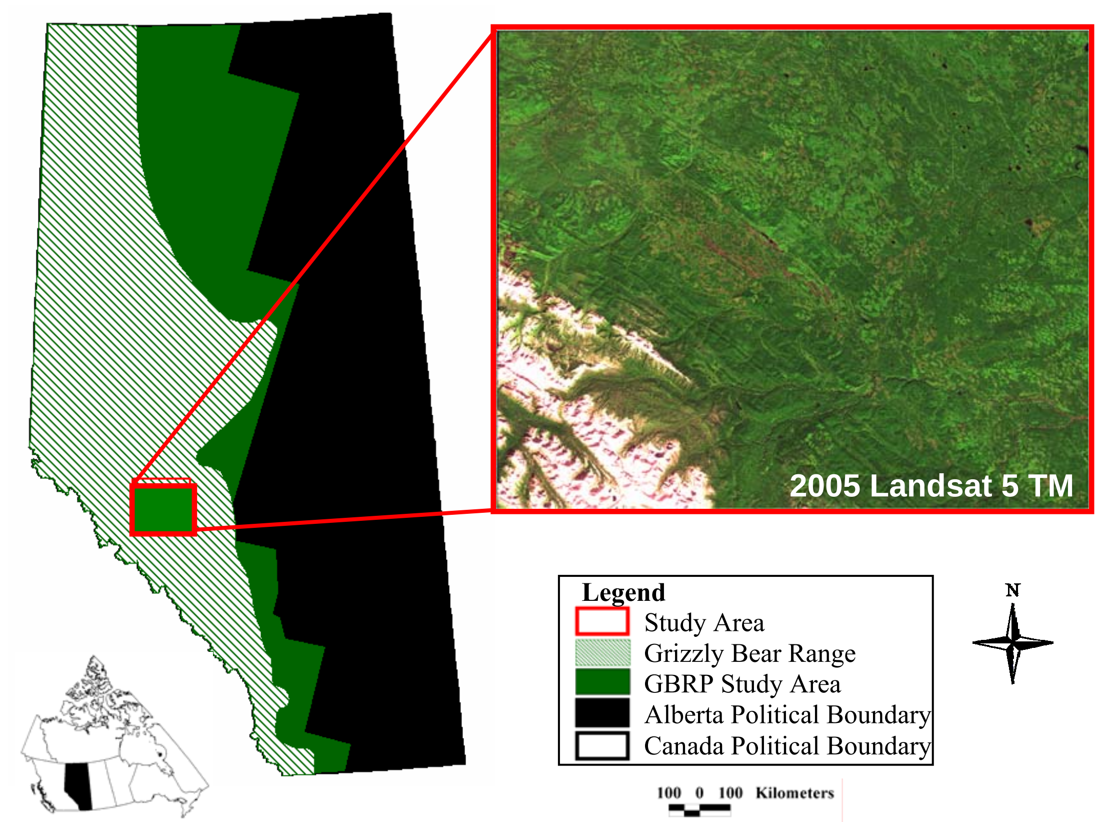

Figure 3.1: Map of Study area and other significant boundaries

Interest is growing within coarse resolution change detection studies (Coppin *et al.,* 2004; Fraser *et al.,* 2005) with phenomena ranging from climate-driven phenology (Moody & Johnson, 2001); natural disturbances (Tansey *et al.,* 2004; Chuvieco *et al.,* 2005) and forest harvesting (Zhan, *et al.,* 2002). Recent attempts use an assortment of change detection techniques including change metrics (Fraser *et al.,* 2005), iterative estimation (Le Hegarat-Mascle *et al.,* 2005), end member and spectral signatures (Thenkabail *et al.,* 2005) logistic regression (Fraser *et al.,* 2003), and decision trees (Zhan *et al.,* 2002). Multi-date differencing has been used in the past (Kasischke & French, 1995) and recently an object-based, coarse resolution classification for burned areas was performed by Gitas, *et al.,* (2004) with positive results. Currently, there are few multispatial change detection studies that use an object-based combination of Landsat TM 30 meter and coarser spatial resolution data.

Since 2000, the Moderate Resolution Imaging Spectroradiometer (MODIS) has been collecting data across the globe every 1-2 days with a spatial resolution ranging from 250 meters to 1000 meters across 36 spectral bands that range from visible to thermal infrared (Townshend *et al.,* 2002; Justice *et al.,*2002). High quality, cloud free mosaics are produced at 16-day intervals and are presently available through the EOS Data Gateway at no cost to the user. These attributes of MODIS make it a prime candidate for multispatial studies with Landsat TM or ETM+ data for the purpose of large-area mapping initiatives.

In an effort to update regional map products, this paper presents a coarse resolution, polygon-based method that utilizes a Landsat-based land cover segmentation classification (described by McDermid, 2005) and 250 meter spatial resolution MODIS NDVI data. We compare the results of the MODIS-based change detection to a GIS-based (manually created) change layer, and also to a Landsat-based change layer produced using the Enhanced Wetness Difference Index (Franklin *et al.,* 2002).

3.3 Study Area

The research is conducted in the Foothills Model Forest (FMF) situated near Hinton, Alberta. The study area covers nearly 10,000 square kilometers and is located along the eastern slopes of the Rocky Mountains in a moderate to high elevation within the existing grizzly bear (*Ursus Arctus)* Research Program (GBRP) study area (**Figure 3.1**). This prime Grizzly Bear habitat is composed of mixed and pure stands consisting primarily of white spruce (*Picea glauca*), lodgepole pine (*Pinus contorta*) and trembling aspen (*Populus tremuloides*) (Stenhouse & Graham, 2005). Extensive land-use activities occurring in this area (for example, oil and gas exploration and forestry) will provide practical examples of change at different spatial scales that are likely to occur within similar forest types (**Figure 3.2**).

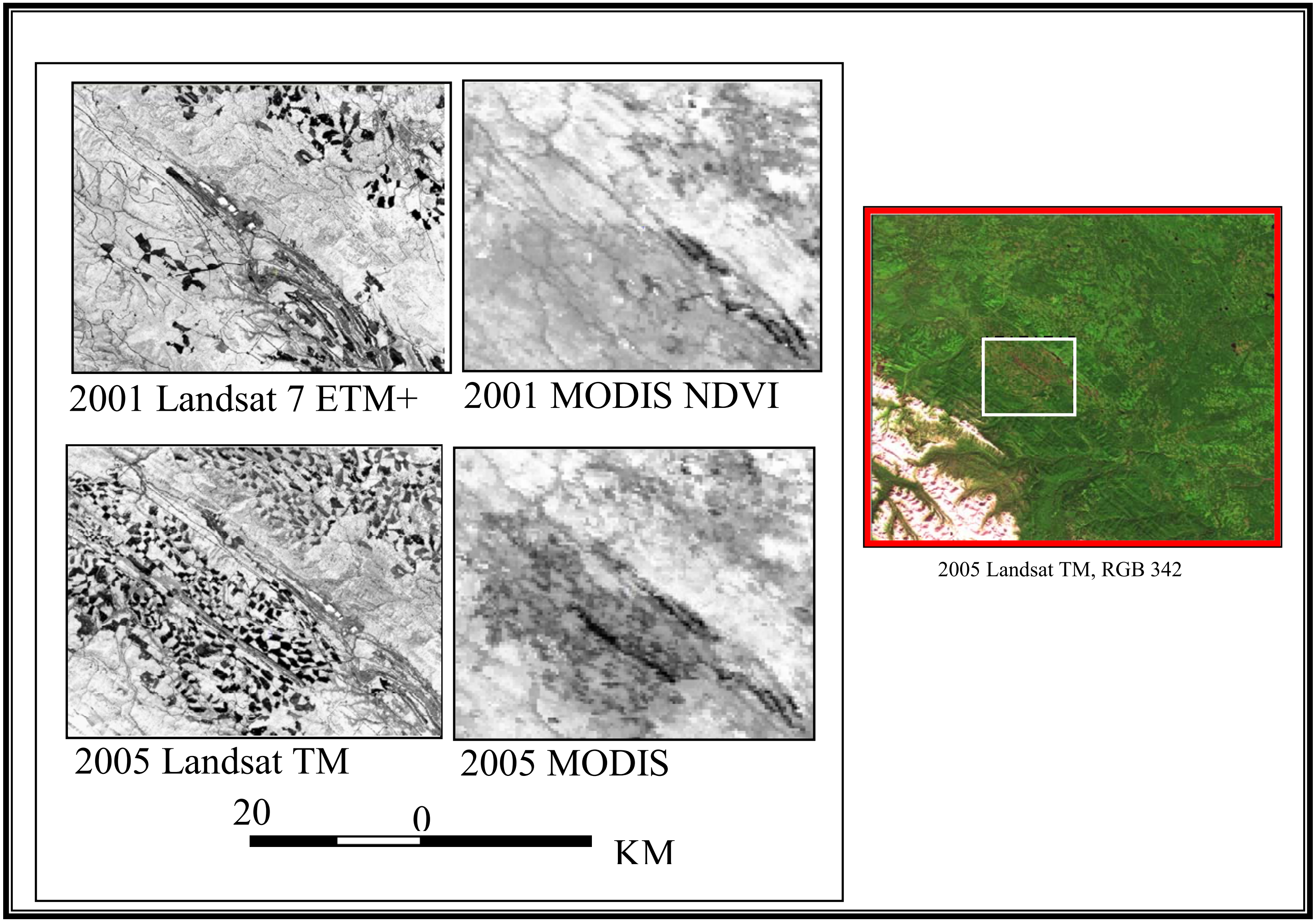

Figure 3.2: Portion of study area subject to intensive land use change

3.4 Imagery Acquisition and Pre-processing

3.4.1 Landsat Data

Based on availability, cloud-free imagery consisting of a Landsat 7 Enhanced Thematic Mapper Plus (ETM+) image from September 14, 2001 and a Landsat 5 Thematic Mapper (TM) image of September 17, 2005 were used to support the Landsat portion of the change detection study. These two images required a radiometric correction to account for illumination angles and atmospheric conditions.

The 2005 Landsat 5 TM image was radiometrically calibrated to convert digital number (DN) to radiance to at-satellite reflectance values consistent to those of Landsat 7 ETM+ using a Top of Atmosphere (TOA) Correction outlined by Chander and Markham, 2003. In order to calculate the TOA reflectance values, the DN's are converted to the original 32-bit radiance values measured by the sensor using the equation:

(Equation 3.1) $$L_\lambda = Gain_\lambda * DN_\lambda + Bias_\lambda$$

Where:

λ	=	TM band number
L_λ	=	at-satellite radiance,
Gain	=	band-specific gain, obtained from the header file,
Bias	=	band-specific bias, obtained from the header file.

Once this calculation is complete and provides the radiance values, at-satellite reflectance is calculated:

(Equation 3.2)

$$\rho = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * sin(\theta)}$$

Where

λ	=	TM band number
L_λ	=	at-satellite radiance
ρ	=	TOA reflectance
$ESUN_\lambda$	=	mean solar exoatmospheric irradiance, and
Θ	=	sun elevation angle, obtained from the header file

In addition to the radiometric corrections, the scenes were geometrically calibrated to eliminate relief displacement, and then re-sampled to a common map projection to ensure precise integration with other data in the GIS. Orthorectification was performed using the satellite orbital math model found in PCI Geomatica OrthoEngine (Toutin, 1995). Ground control points (n=25) were collected using a government-issued roads layer, and a 30m DTMI digital elevation model (DEM). The resulting second-order polynomial produced a root mean square error (RMSE) <0.50 pixel. The image data were resampled using a nearest neighbor algorithm to produce a 30m grid projected to UTM Zone 11, NAD83 datum based on the GRS80 ellipsoid. Following visual inspection of geometric quality based on existing roads, clear cuts and other linear features, the data were clipped to the final study area of 3114 by 2519 pixels covering a total area of 7062km^2.

Once the final image was prepared, the wetness index of the tasselled cap transformation was calculated for the at-satellite reflectance of both the Landsat 7 ETM+ (Crist and Cicone, 1984) and the Landsat 5 TM imagery (Huang *et al.,* 2000). This index for the two datas was used to generate the Enhanced Wetness Difference Index based on the study by Franklin *et al.,* (2001). Shown here are the Landsat TM coefficients, where LS_{Band*} refers to the individual reflective Landsat bands:

(Equation 3.3) $$Wetness\ Index = (0.2626*LS_{Band1}) + (0.2141*LS_{Band2}) + (0.0926*LS_{Band3}) + (0.0656*LS_{Band4}) + (-0.7629*LS_{Band5}) + (-0.5388*LS_{Band7}).$$

3.4.2 MODIS Data

Moderate Resolution Imaging Spectroradiometer (MODIS) 250 m spatial resolution Normalized Difference Vegetation Index (NDVI) data were obtained for each year from 2000 to 2005 as outlined in **Table 3.1**. The study area is contained in tile 10v03. MODIS products are atmospherically corrected before release, therefore, preprocessing was limited to: 1) reprojecting the sinusoidal projection to UTM Zone 11 (NAD 83), 2) translating the dataset to a usable file format and, 3) clipping the mosaic to fit the study area. These tasks were completed using the MODIS Reprojection Tool (MRT) downloaded from the NASA Land Processes Distributed Active Archive Center.

Table 3.1: Satellite imagery acquisition dates

YEAR	MODIS	LANDSAT
2001	August 13	September 14
2002	July 29	
2003	August 13	
2004	August 13	
2005	July 28	September 17

3.4.3 Manual GIS Change Layer (ΔGIS)

A reference change layer – called ΔGIS – was compiled based on existing clear cut and wellsite data stored in the FMF GBRP data archive. The archive consists of various datasets consisting of vector layers, aerial photographs, satellite imagery, and vegetation ground data that are acquired from industrial partners including forestry companies, oil and gas companies, the provincial government, non-governemnt organizations. Some of these products are also developed by project team memebers. Typically, each data product provides partial coverage across the entire GBRP study area. For example, cutblock layers within the database are based on Forest Management Areas (FMAs) and often, only larger companies have this data digitally available and are willing to share it. In order to create ΔGIS, the available cutblock and wellsite data were compiled to cover most of the area. To complete the reference change layer (ΔGIS), some manual digitizing of change based on image interpretation of the available aerial photographs and high resolution SPOT5 imagery (acquired July, 2005) in the data archive was necessary. Additionally, the 2005 Landsat TM image was used to digitize remaining change areas that did not have other data coverage. This amounted to less than 10% of the entire area.

In this interpretation, features such as roads, well sites and clear cuts were readily identified. In order to accomplish accurate, reliable manual labelling of change, extensive *a priori* knowledge of the characteristics of the pixels or groups of pixels for each class was required; this was accomplished through multiple field observations designed to identify each change mapped in the GIS database. These field observations were acquired by interdisciplinary field teams assembled for the purpose of training data acquisition and verification of the land cover classification. Typically, manual interpretation of change is confirmed in the form of experience and/or ancillary data which includes other classification maps, GIS layers, ground truth data, aerial photography, etc. Despite some error associated to change omission (**Figure 3.3**), the GIS-based change layer (ΔGIS) was used as the reference layer for the study.

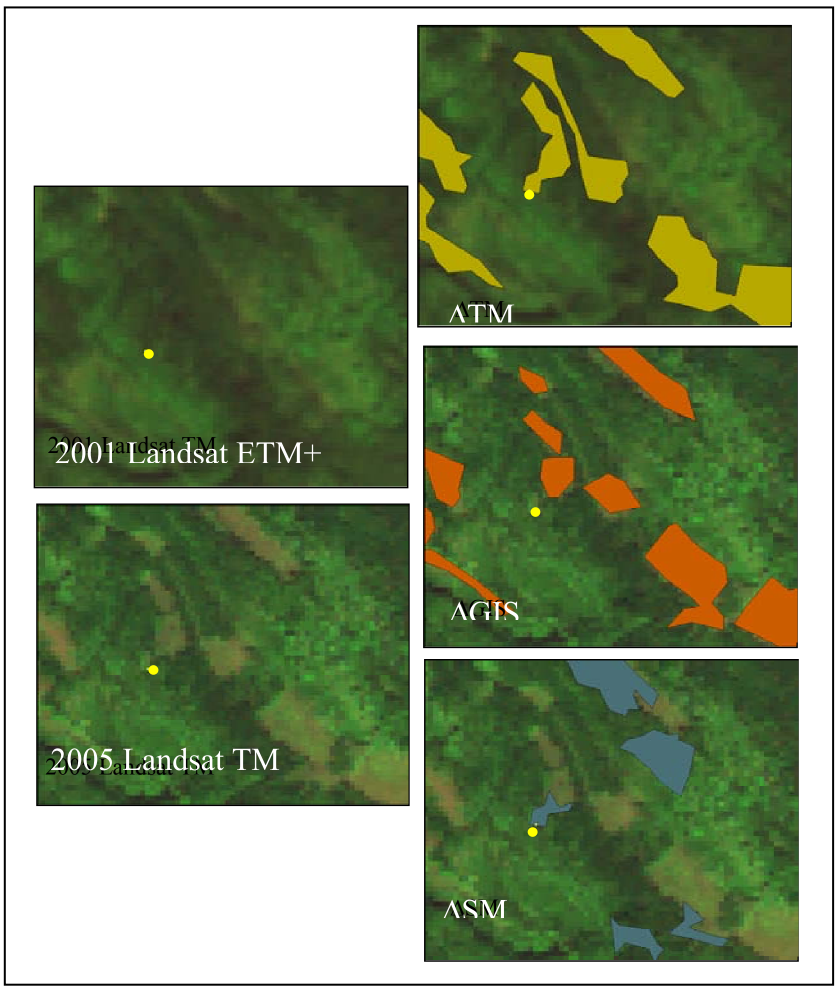

Figure 3.3: Error of Omission found in ΔGIS. One 'No change' training point (yellow dot) as determined by the polygons within ΔGIS is placed in an area detected as change by both ΔTM and ΔSM, possibly missed by the manual methods used.

3.5 Image Differencing Methods

A series of one-year and five-year change maps were created using the 2000-2005 imagery to create a number of different change layers for further testing (**Table 3.2**).

Table 3.2: Dates of Image Differencing

	YEAR 2				
YEAR 1	**2001**	**2002**	**2003**	**2004**	**2005**
2000	ΔM1				
2001		ΔM2			
2002			ΔM3		
2003				ΔM4	
2004					ΔM5
2005	ΔTM & ΔSM				

In order to create the polygon-based change detection layers for comparison, several steps were required. First, a polygon layer of the study area was clipped from the eCognition-derived segmentation of the FMF GBRP's Landsat TM and ETM+ orthomosaic base land cover map. Second, the MODIS NDVI values were applied to the polygon layer using the VIMAGE command in PCI Geomatica's Algorithm Library. This algorithm created a polygon layer of average mean NDVI MODIS values for each individual polygon within the study area (**Figure 3.4)**. Third, the layers were subtracted (YEAR 1 - YEAR 2) as outlined in **Table 3.2** resulting in 7 separate layers of change/no change. Fourth, the one-year maps were then merged together resulting in a five-year cumulative change layer; then, a five-year single image change detection was completed using a image differencing of the 2001 and 2005 NDVI MODIS imagery (**Figure 3.5**).

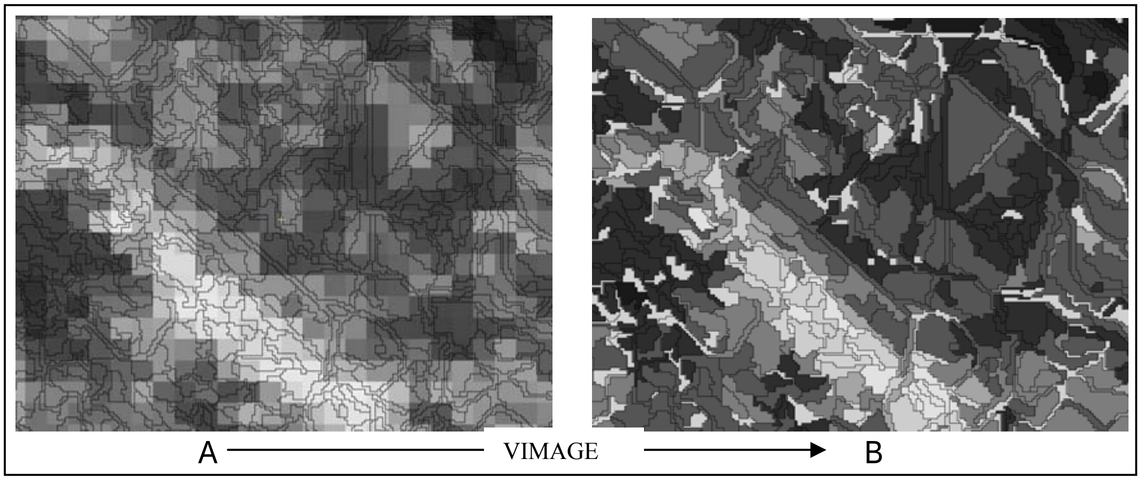

Figure 3.4: Conversion from a pixel-based image to a polygon-based image. A) MODIS NDVI 250m pixels with polygon overlay B) Mean NDVI Polygon-based MODIS 250m data derived from PCI Geomatica's VIMAGE algorithm

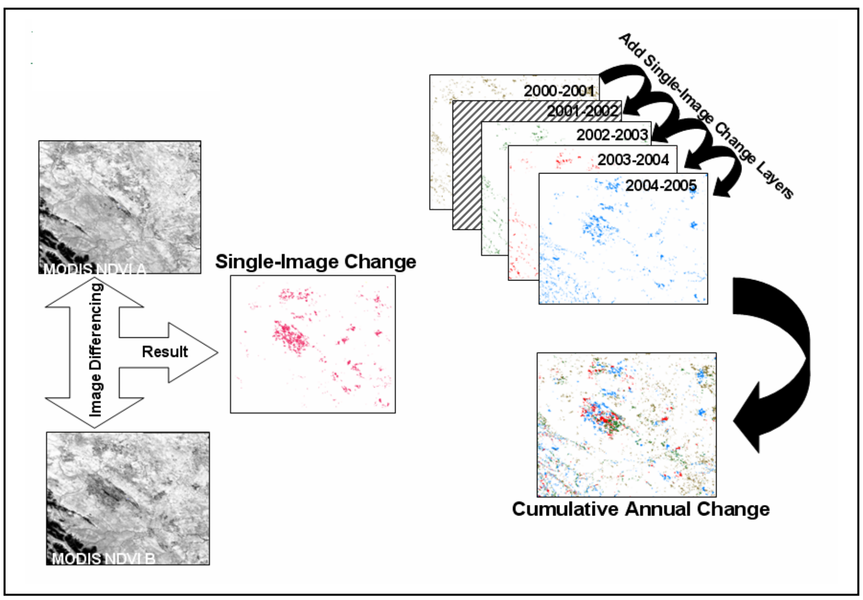

Figure 3.5: Creation of the Single-Image and Cumulative Change Detection Layers

The fifth step, and one of the most crucial was thresholding – determining the value(s) of actual change instead of differences that may be a result of sensor noise, atmospheric differences, geometric error, or other non-land-cover change source. For this process, earlier work by Franklin *et al.,* (2005) suggested that selecting a threshold of two standard deviations from the mean (i.e., mean difference in pixels of change polygons) resulted in an appropriate change threshold for Landsat TM or ETM+ Enhanced Wetness Difference Index studies of forest canopies. Visual inspection of the resulting 'thresholded' imagery suggested that this was an adequate reference point for this MODIS study; future work, however, may be necessary to generate optimal threshold values for the changes to be mapped.

These steps were performed with the Landsat EWDI and the MODIS NDVI products. Upon completion of the final change layers (MODIS 2001-2005 known as ΔSM, plus cumulative MODIS change 2001-2002, 2002-2003, 2003-2004, 2004-2005, known as ΔCM plus Landsat 2001-2005, known as ΔTM, several accuracy and map comparison tests were performed to evaluate the quality of the MODIS change detection (ΔCM and ΔSM) and Landsat EWDI change detection (ΔTM) compared to the GIS-based change layer (ΔGIS) of the same area.

3.6 Accuracy Assessment

Creating the sampling strategy for assessment points posed a challenge and therefore, several sampling strategies were implemented for the accuracy assessment. First, a proportional sample was selected; i.e., a random selection of polygons was generated. This resulted in extremely high accuracies overall due to the mis-proportion of change:no change (4:96). In other words, too much of the image had not changed and a direct proportional sample was biased to those no-change areas.

A different sample strategy was needed to ensure that enough change polygons were selected; therefore, in order to represent all types of change within the area, one training point was assigned to each change polygon contained within ΔGIS (n=1418). The accuracy of the Change class was of primary interest in this study (i.e., the occurrence of omission error was thought to be of greater consequence), it was important to ensure the number of points representing 'no change' did not falsely improve the overall map accuracy. No Change points (n=400) were randomly generated within ΔGIS. This sample size was chosen based on a study by Congalton (1991) who suggested that increasing the sample size beyond this point does not make a significant difference. To avoid the effects of mixed-pixels and confusion along edges, especially within the coarse resolution pixels, each of the points was placed at least 400m from the edge of change polygons (equivalent to approximately 1.5 MODIS pixels). This sampling strategy ensured that all types of change were represented in the sample.

Using the sample points, both validity and reliability were assessed. First, validity - the agreement between the value of a measurement and its true value on the ground – was tested using a confusion matrix for each ΔCM, ΔSM, ΔTM with the reference map ΔGIS. The matrix was then used to determine the overall map accuracy, error of omission, and error of commission. Next, reliability - or the reproducibility of the maps-was assessed by calculating KAPPA:

(Equation 3.4) $$k = \frac{\pi_o - \pi_e}{1 - \pi_e}$$

Where:

π_e = expected probability of agreement

π_o = actual agreement

The KAPPA calculation produces an index that compares agreement with chance and can be thought of as the chance-corrected proportional agreement. Possible values range from +1 (perfect agreement) to 0 (no agreement above that expected by chance) to -1 (complete disagreement). Landis and Koch (1977) suggest the following for one possible interpretation of KAPPA:

- Poor agreement = Less than 0.20
- Fair agreement = 0.20 to 0.40
- Moderate agreement = 0.40 to 0.60
- Good agreement = 0.60 to 0.80
- Very good agreement = 0.80 to 1.00

In addition to the accuracy assessments mentioned above, a map classification comparison was performed. This test provides insight into how actual spatial coverage of change polygons (ΔSM and ΔTM) compare to polygons of ground data (ΔGIS). This assessment provided a different perspective on the accuracy because 1) information concerning the association among specific individual classes in a confusion matrix can be lost by summary association measures and; 2) this test provided a spatially explicit comparison.

Next, the Cramer's V correlation coefficient (V) was calculated. A statistical correlation coefficient such as this is used to measure the relationship between two categorical variables. The Cramer's V represents this association or correlation with values ranging from 0 (no association) to 1 (perfect association) (Davis, 1986; Dickson, 2000). Additionally, the Cramer's V statistic is not affected by sample size and therefore is very useful in situations where one may suspect a statistically significant chi square was the result of a large sample size instead of any substantive relationship between the variables.

One study by Klita *et al.* (1998) compared AVHRR and Landsat TM classifications of a boreal forest in Northwest Alberta using the Cramer's V. One other comparative study by Fosnight and Fowler (2001) used this statistic to compare an AVHRR-based US Land Cover Characterization and a photo-based USGS Land cover and Land Use map. The AVHRR data was scaled to match the spatial scale of this classification and cross tabulation from the two differing data sets tested several measures of association and agreement. These included: KAPPA, Cramer's V, Guttmans;s Proportional Reduction in Error, Goodman and Kruskal's Proportion of Explained Variance, and Percent Correctly Classified. For rectangular cross classified tables, the Cramer's V performed in the top 3 and authors suggested that Cramer's V be used as a test of independence between two classifications and strength of association determined by Guttman's Proportional Reduction in Error and Goodman and Kruskals's Proportion of Explained Variance (Fosnight and Fowler, 1996). It is calculated as:

(Equation 3.5) $$V = ((X^2/N(L-1))^{1/2}$$

Where:
X^2 = Chi Square,
N = the total number of observations in the contingency table,
L = the minimum number of rows or columns in the contingency table.

3.7 Results and Discussion

The results of the change detections are displayed in **Figure 3.6**. Overall, spatial representation of the changes detected by MODIS and Landsat agree generally with those mapped in the GIS (**Figure 3.6A**). The general pattern of change is apparent, through the Landsat (ΔTM) (**Figure 3.6C**) and the MODIS change layers (ΔCM and ΔSM) however, the latter appear to contain more errors of omission and errors of commission (**Figure 3.6B** and **Figure 3.6D** respectively).

Closer inspection of a small area reveals some interesting details in the change detection output (refer to **Figure 3.7**). Significant omission is apparent (see **Figure 3.7** identified with the number 1 in the top central part of the right hand map); here, the GIS contained a large polygon identified as change which was not captured in either of the MODIS change detection procedures. In the second part of the figure (lower central, labelled as the number 2), partial change detection appears to have occurred – here, the GIS data suggest several polygons were missed but that others were quite accurately identified in the MODIS procedure. And finally, in the lower right hand side of the

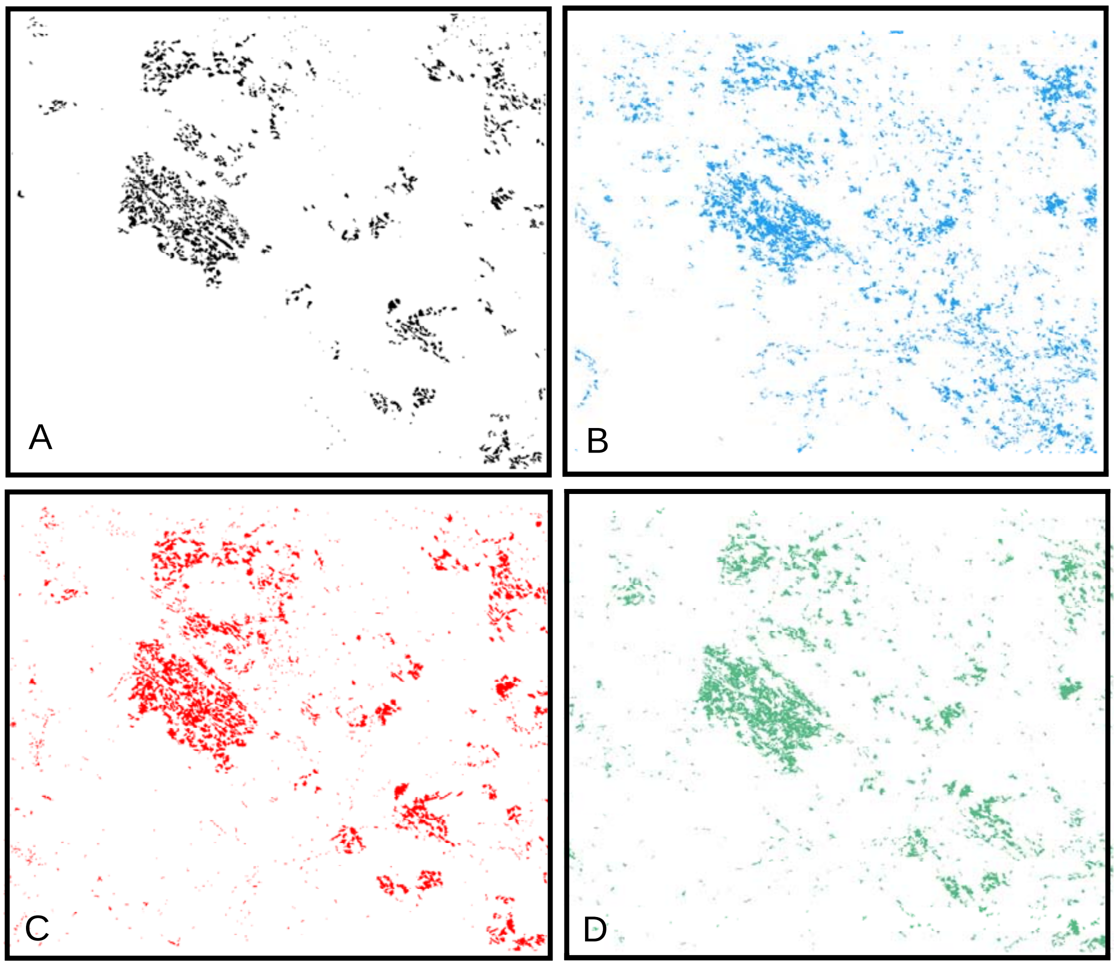

Figure 3.6: Change Detection Results:
A) Manual Change: ΔGIS, B) Cumulative MODIS NDVI Change: ΔCM, C) Single Image Landsat TM EWDI Change: ΔTM, D) Single Image MODIS NDVI: ΔSM.

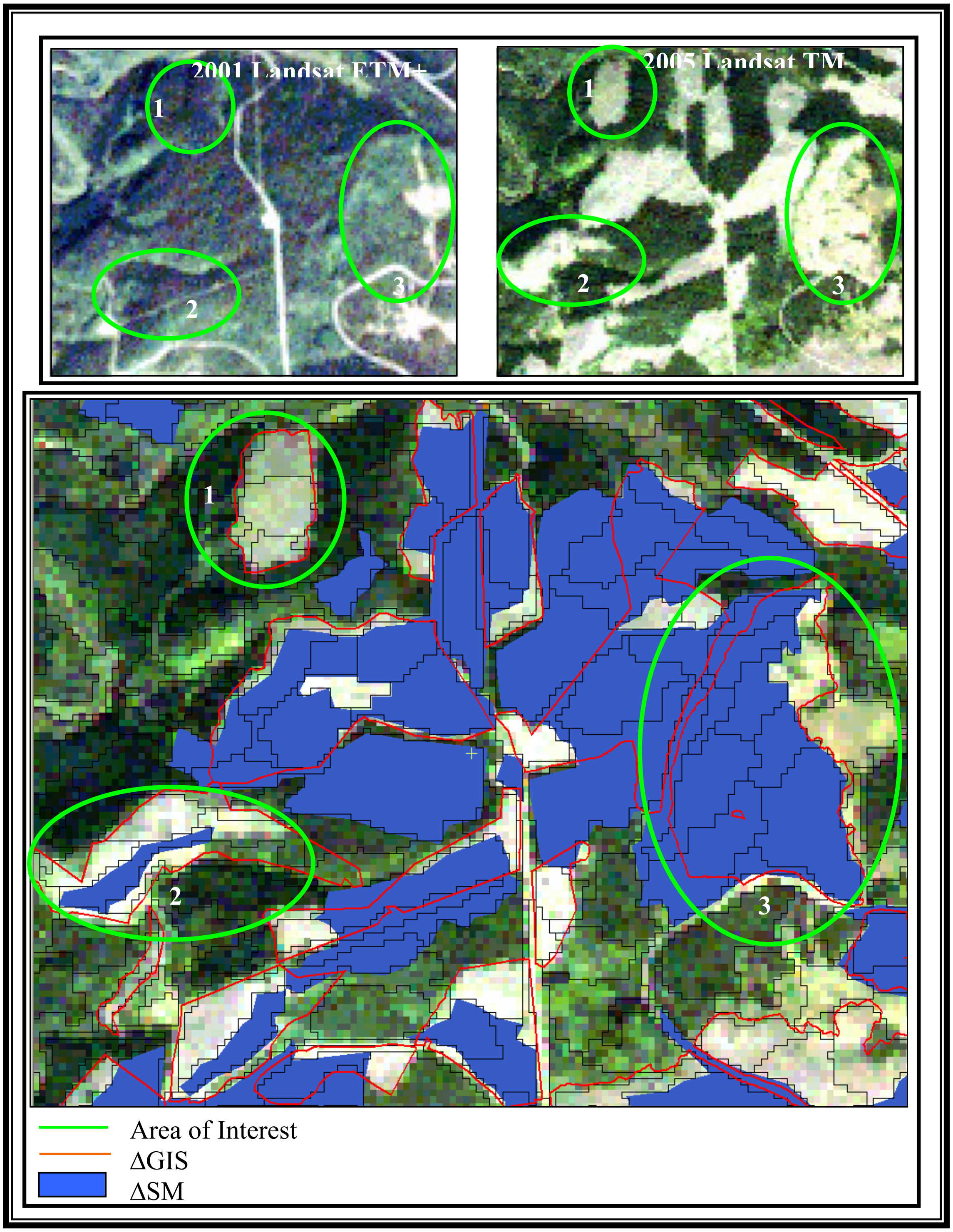

Figure 3.7: An example of change detected wthin ΔSM (bottom) compared with 2001 Landsat 7 ETM+ (top left) and 2005 Landsat 5 TM (top right). Highlighted areas include 1) no change detected 2) partial change detected and 3) almost perfect change detected

figure (labelled as number 3), very accurate change detection appears to have occurred since the GIS polygons appear to overlay almost perfectly the change polygons identified in the MODIS image differencing. Some of the errors may be partially attributed to the poorer quality of the early V003 MODIS datasets from 2000 and 2001; unexpectedly, annual seasonal variations may also factor in the poor quality data set.

Using the photo interpreted reference data derived from ΔGIS (n=1418), a series of accuracy assessments were performed to validate and test map agreement. Accuracy change statistics were reported for each of the following: 2000-2005 NDVI Single Image MODIS change detection (ΔSM), 2001-2005 and 2000-2005 NDVI Cumulative Image MODIS change detection (ΔCM) and, the Landsat TM change detection (ΔTM). **Table 3.3** provides the results of the confusion matrix and **Table 3.4** summarizes the overall map accuracies, error of omission and commission and KAPPA. Each of these values are supplemented with a 95% confidence interval and a ρ-value of <0.01 indicating high significance.

ΔTM yielded approximately 84% (+/- 1.7%) accuracy when compared to the ΔGIS. This is consistent with the accuracies reported in earlier change detection studies in New Brunswick (Franklin *et al*., 2002), and in the Pacific Northwest USA (Cohen *et al* 1998). The highest map accuracy for the MODIS change detections, from ΔSM, was 59.4% (+/- 4.1%) and a KAPPA of 0.27 (+/-0.040). The majority of the errors correspond to change omission (0.51). This indicates that the true area of change is likely being underestimated since almost half of the change pixels are not being correctly classified (Lunetta *et al.,* 2004; Jensen, 2005). Commission errors were also reasonably high for the no-change class likely due to the misrepresentation of the change class and the large sample size. ΔCM resulted in an overall map accuracy of 52.0% (+/- 6.5%) with a KAPPA of 0.199 (+/- 0.039), these values are slightly lower than with ΔSM and also have a higher omission error. This indicates that ΔSM is more accurate and reliable for detecting change for this study and therefore, ΔCM will not be used for further analysis the remainder of the accuracy tests will only be applied to ΔSM.

Table 3.3: Results of the Confusion Matrix

	ΔGIS Observations					
		No-Change	Change	Total	% Correct	% Commission
Remote Sensing-Based Observations	ΔCM					
	No Change	**391**	**852**	**1243**	**31.5**	**68.5**
	Change	**9**	**566**	**575**	**98.4**	**1.6**
	Total	**400**	**1418**	**1818**		
	% Correct	**97.8**	**39.9**		**52.6**	***κ***
	% Omission	**2.3**	**60.1**			**0.21**
	ΔSM					
	No Change	**379**	**717**	**1096**	**34.6**	**65.4**
	Change	**21**	**701**	**722**	**97.1**	**2.9**
	Total	**400**	**1418**	**1818**		
	% Correct	**94.8**	**49.4**		**59.4**	***κ***
	% Omission	**5.2**	**50.6**			**0.27**
	ΔTM					
	No Change	**394**	**274**	**668**	**59.0**	**41.0**
	Change	**6**	**1144**	**1150**	**99.5**	**0.50**
	Total	**400**	**1418**	**1818**		
	% Correct	**98.5**	**80.7**		**84.6**	***κ***
	% Omission	**1.5**	**19.3**			**0.64**

Table 3.4: Map Accuracy and Confusion Matrix Descriptive Statistics

LAYER	MAP ACCURACY	KAPPA	CHANGE Error of Omission	CHANGE Error of Commission
ΔSM	0.594 (=/- 0.041)	0.272 (+/- 0.0395)	0.506 (+/-0.027)	0.0291 (+/-0.013)
ΔCM	0.520 (+/- 0.065)	0.199 (+/- 0.0385)	0.601 (+/-0.026	0.0358 (+/-0.016)
ΔTM	0.846 (+/-0.017)	0.638 (+/-0.0390)	0.193 (+/-0.021)	0.00522 (+/-0.0046

3.7.1 Map Agreement Comparison

The map agreement comparison spatially compared each of the ΔSM and ΔTM products to the control, ΔGIS. The purpose of this test is to compare actual spatial coverage of each ΔSM, ΔTM and ΔGIS where previous evaluations focussed on a data point set. The results of the comparison are displayed in **Figure 3.8** and **Table 3.5**. The largest difference was found between ΔSM and ΔGIS. However, the results show that ΔSM was able to detect over half of the actual changes (11887/21927 hectares or 54%) included in the ΔGIS and 96% of the total No Change included in ΔGIS. The ΔSM change detection included an additional 26792 hectares or 3.79% of change and was not able to detect 10041 hectares or 1.42% compared to that within the ΔGIS. This produces an overall discrepancy of only 5.21% across the entire area (36833 hectares). Obviously, the larger pixel size of the MODIS data has created a similar area of change even though the number of no change locations has been reduced (omitted).

Comparatively, ΔTM was able to detect 18361/21927 hectares, or 83.87% of the total change and 669547/684274 hectares, or 97.84% total No Change found within the ΔGIS. It still is not able to detect perfectly 100% of the change that was found by manual interpretation and GIS data layers, however, there is only a discrepancy of 2.6% or 18294 hectares across the entire area, less than half of the error associated with the ΔSM.

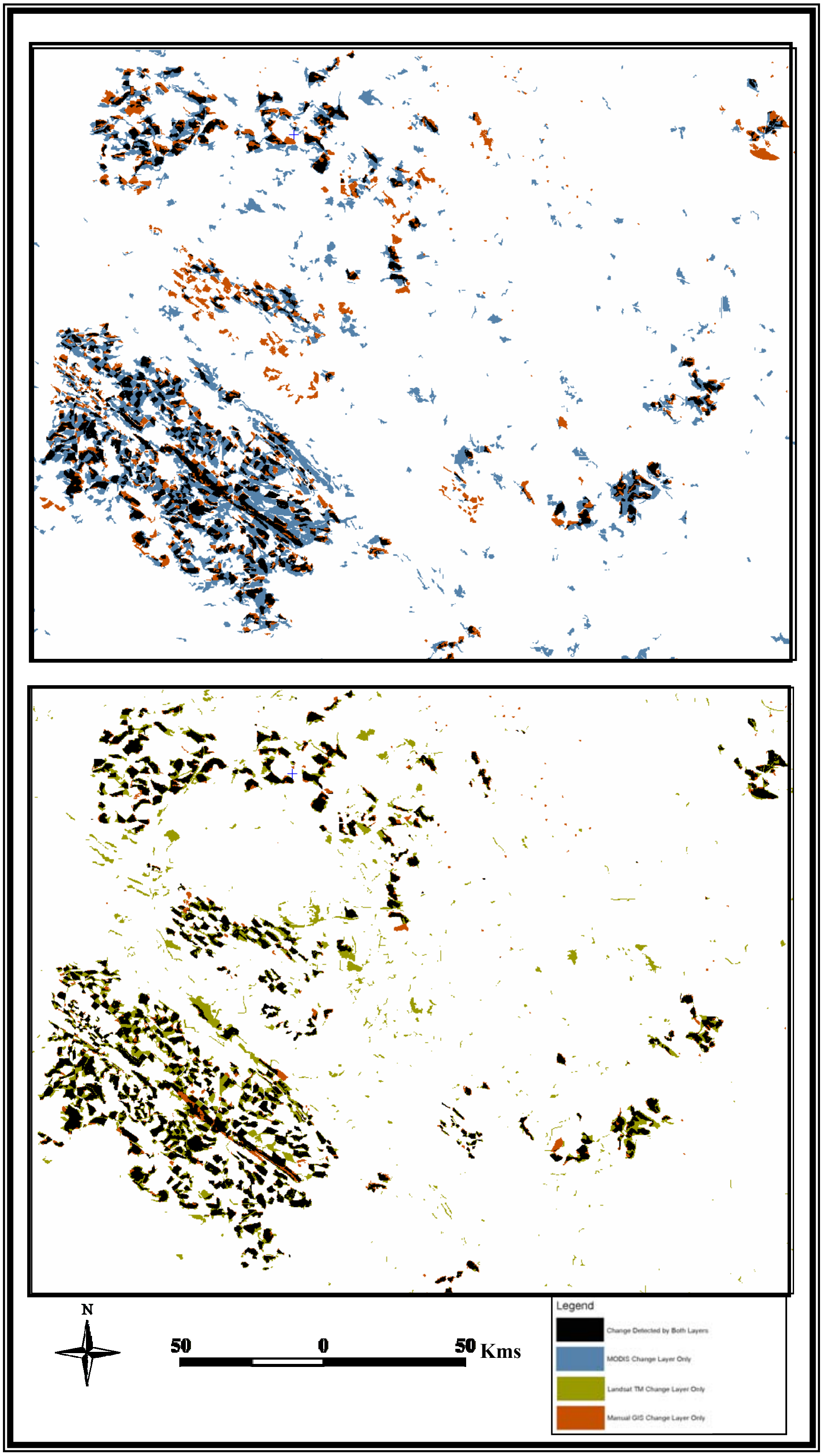

Figure 3.8: Spatial Agreement between ΔTM and ΔSM with ΔGIS. Black areas indicate areas of perfect agreement

Table 3.5: Map Agreement Comparison - Total Area (Ha) for Individual Layers

TOTAL AREA (HA) OF STUDY AREA		
	ΔGIS ** vs ΔTM*	**ΔGIS ** vs ΔSM***
"NO CHANGE" AGREEMENT	669547(94.81%)	657482 (93.1%)
"CHANGE" AGREEMENT	18361(2.6%)	11887 (1.68%)
DATASET 2** "CHANGE" MISSED BY DATASET 1*	3566(0.51%)	10041 (1.42%)
DATASET 1* "CHANGE" MISSED BY DATASET 2**	14728(2.09%)	26792 (3.79%)

3.7.2 The Map Agreement Comparison and the Cramer's V Statistic

The results of the Map Agreement Comparison and the Cramer's V statistic are displayed in **Table 3.6**. Cramer's V values show significant agreement between the ΔSM and ΔTM with ΔGIS, 0.38 and 0.67 respectively. This value is fairly low for the MODIS detection and closer to no association (Cramer's V = 0) than to complete association (Cramer's V = 1.00). However, if ΔTM is normally accepted as the best replacement to ΔGIS, (Cramer's V=1.00), a different interpretation is that the maximum Cramer's V is 0.67 instead of 1.00. This indicates that the association is more likely 0.38 out of a possible 0.67 resulting in a "weighted" Cramer's V of 0.57.

Table 3.6: Map Agreement Statistics: Cramer's V and Contingency Coefficient

Comparison	Cramer's V	ρ
ΔSM vs ΔTM	0.431	<0.01
ΔGIS vs ΔTM	0.670	<0.01
ΔGIS* vs ΔSM	0.383	<0.01

3.7.3 Natural Breaks Classification

Because the overall accuracies achieved in this study were not as high as desired - most remote sensing products strive for an overall map accuracy of >80% - a fourth test was performed in order to determine if there is a minimum polygon size for change to be accurately identified with the 250m spatial resolution MODIS sensor. Change polygons and their associated validation points from ΔGIS were distributed into 13 size classes based on natural breaks as decided by the software package ArcGIS 9. The size classes are summarized in **Table 3.7**. The No Change polygons were excluded as we are only interested in the size at which changes can accurately be detected. As anticipated, there is an increasing trend in the overall change class accuracy based on MODIS data with increasing polygon size (**Figure 3.9**). The error of omission decreases consistently to 0% in the classification for the largest class; the smallest class (in area) is the least accurate as expected. The error of omission appears to level off to approximately 0.21 with size classes 6 and 7 (14.5-19.2 hectares and 19.2-24.5 hectares); one interpretation of these results is that change polygons of approximately 15 hectares may be the optimal size for successful detection of change features using MODIS data. At this point, the error of commission also decreases slightly, at least until Class 11, at which point the error of commission does increase significantly.

Unfortunately, this is the point in the sample at which the numbers of training data within each natural breaks class are quite low, and therefore, this could significantly affect the error of commission associated with the Change class.

Table 3.7: Natural Break Polygon and Training Point Distribution based on Size of Change Polygons

Class	Polygon Size (ha)	Number of Change Points	Accuracy ΔSM versus ΔGIS	Error of Omission	Error of Commission
1	0-2.9	266	65.5	0.767	0.30
2	2.9-5.3	115	69.3	0.583	0.31
3	5.3-7.9	128	72.6	0.578	0.27
4	7.9-10.9	106	76.8	0.453	0.30
5	10.9-14.5	117	77.2	0.402	0.31
6	14.5-19.2	140	79.4	0.321	0.27
7	19.2-24.5	132	81.9	0.311	0.21
8	24.5-31.9	124	81.1	0.306	0.22
9	31.9-41.8	107	85.4	0.336	0.23
10	41.8-54.8	84	85.9	0.107	0.27
11	54.8-77.6	64	86.9	0.219	0.26
12	77.6-110.5	24	93.1	0.114	0.34
13	110.5-311.3	11	93.7	0.000	0.70
TOTAL		1418			

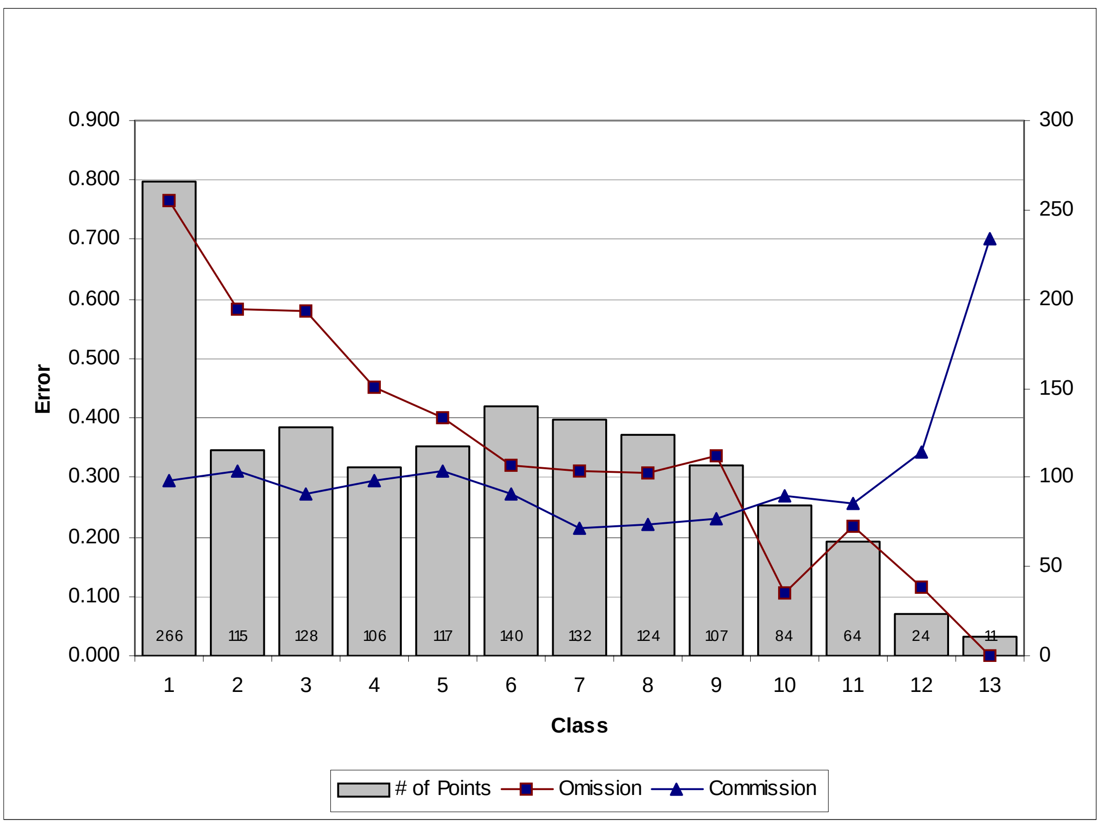

Figure 3.9: Data Point Distribution of the Natural Breaks Classes vs 2001-2005 ΔSM Error Statistics

In an attempt to overcome this problem, the original segmentation used for the change detections was used to apply a size class to each of the 400 No-Change points. This did improve the results for all map agreement tests, however, the overall trend did not change as expected. One reason may be that the polygons within the segmentation do not match perfectly with ΔGIS and therefore, the overall area of change is affected (**Figure 3.10**). Secondly, since the scale of the segmentation was preset to 10 ha, this effectively limits the representation within the larger size classes; for example, for class 13 (polygons over 10 hectares), n=5 , and even a small difference has a large impact on the results. In summary, however, the users of the map are most interested in overall accuracy on the ground, and therefore, would likely prefer to use ΔGIS as the reference map.

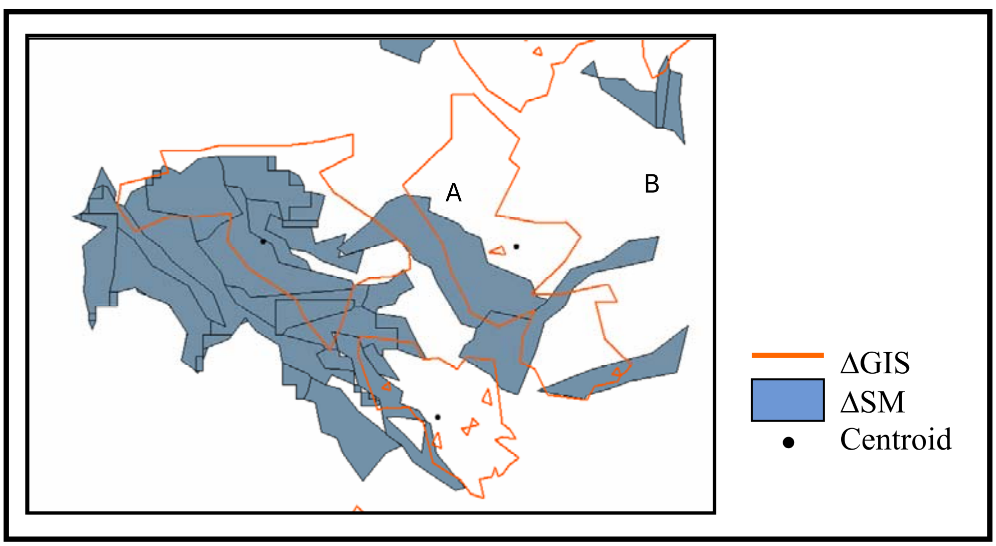

Figure 3.10: Partial detection due to ΔGIS polygon centroid location. Polygon A shows agreement between ΔSM and the ΔGIS. Polygon B is an example where partial change was detected by ΔSM however, the location of this ΔGIS polygon centroid is outside of the change area and therefore excluded in the confusion matrix accuracy assessment.

3.7.4 Thresholding Issues

Thresholding has long been an issue within satellite imagery change detection studies, and the present study is no exception – the results presented here are very sensitive to the selection of the threshold, as the mapper is trying to balance the detection of 'too much change' versus missing actual change features on the ground. The ability to select an appropriate threshold of change to exclude undesired 'noise' determines the success of the change detection. Typical methods are based on qualitative choices, for example, airphoto interpretation (Mas, 1999), field methods, and individual expertise (Lyon *et al.,* 1998). Few studies are available within the literature that use more quantitative methods, however, one study by Franklin *et al.,* 2005 found that using two standard deviations from the mean was appropriate for detecting forest change of an EWDI Landsat TM study with 85% accuracy. This was used as the basis for the thresholding in the present study, however, qualitative, manual adjustments were required for best results and more work is needed to determine the appropriate threshold for use in this application. It is possible that higher overall accuracy in the MODIS change detection procedures could be obtained with a different thresholding technique. The results presented here are internally consistent since the same two standard deviation threshold was applied in all change layer procedures.

3.7.5 The Influence of Segmentation

Figures 3.10 and 3.11 suggests one additional problem when applying coarser satellite resolution data sets to a polygon-based map update. The GIS polygons are shown in red, and the underlying polygons are those mapped using the segmentation procedure on the original Landsat imagery – clearly, there are major questions associated with the appropriateness of the Landsat-based polygons as 'identifiable' features when the GIS polygons are mapped as change. This problem is made even more difficult to resolve when the larger pixel sizes of the MODIS data set are incorporated in the change update.

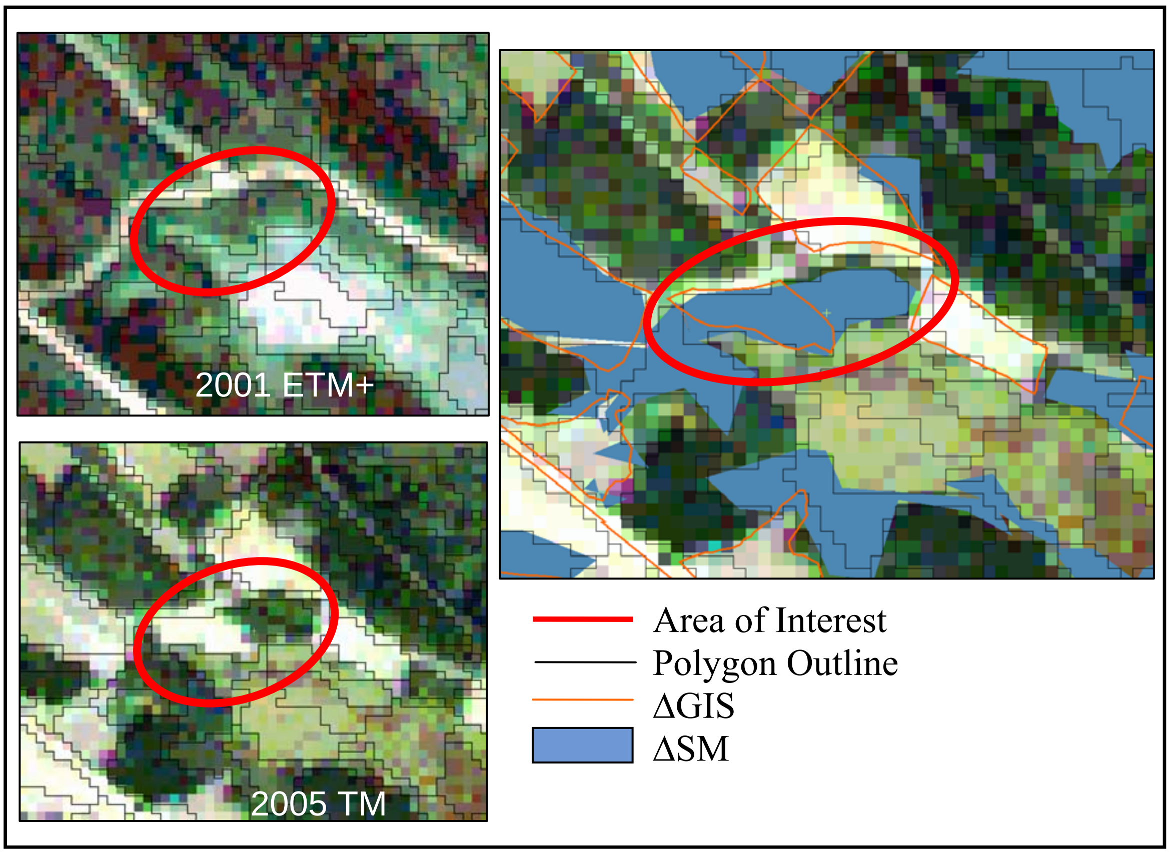

Figure 3.11: Example where size and shape of polygon affects the polygon-based method

3.8 Conclusion

In this paper, we detected change using low resolution MODIS sensor data and applied these changes to land cover polygons created by segmentation of Landsat data. A conventional image differencing was performed annually (cumulative 2000-2001, 2001-2002, 2002-2003, 2003-2004, 2004-2005), and in a 6 year interval (2000-2005). The resultant change layers were subject to thresholding to minimize noise and resulting in a set of polygon-based MODIS change detection features. Similarly, an EWDI change detection was performed on Landsat TM imagery of the same area from 2001-2005, and a manual change layer based primarily on GIS data and image interpretation skills was compiled for comparison purposes. Change was detected using the polygon-based MODIS method with approximately 59% accuracy across the map; the TM-based procedure yielded approximately 85% accuracy. The MODIS change detection accuracy was higher than expected as the resolution of the MODIS is over 8 times less than that of Landsat TM. The greatest sources of error reported were the relatively large omission errors in small change polygons, indicating that the amount of MODIS detected change was underestimated. These errors can be attributed to three main issues: 1) threshold selection, 2) pixel location, 3) differences in spatial resolution.

Across the study period (6 years), approximately 3.1% or 21927 hectares of the area was altered by anthropogenic changes. Of these changes, 1.68% were detected by the MODIS sensor, however, an additional 3.79% or 26792 hectares were included because of the larger pixel size. The use of the original polygons was a more appropriate mapping strategy. The single-image change detection provided the best results, possibly because of cumulative data problems (e.g., atmospheric effects) in comparing imagery year-by-year over the five-year interval. Also, it is possible that some of the first forest clear cuts were created shortly after initial image acquisition and were maturing by the time of sequential image collection resulting in weaker spectral changes (Lunetta *et al.,* 2004). The results of this study show that using MODIS 250 meter spatial resolution data are not as effective at determining accurate, detailed change across forested landscapes as Landsat. However, the larger, more general area changes (>15ha) were detected quite accurately, thereby providing a basis for further research and identifying areas where higher spatial resolution imagery are required.

3.9 Acknowledgements

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3.10 References

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4.0 SYNTHESIS AND RESEARCH APPLICATIONS

The results of this research are a strong contribution that can be considered of significance in terms of two key areas: 1) remote sensing map update and 2) large-area mapping of wildlife habitat and landscape structure. In this final chapter, the use of the map products is described briefly as an input to landscape fragmentation analysis, which is an essential environmental management concern in many areas of the world. This final chapter provides not only a synthesis of the important contributions of this thesis research, but also outlines possible suggestions for future research initiatives.

4.1 Significant Research Contributions

This research study developed a procedure for updating existing high and moderate spatial resolution, large-area land cover mapping products using a multiple-scale change detection technique. The method compared GIS database maps of environmental change to those available from higher spatial resolution Landsat imagery and coarser resolution imagery acquired by the MODIS sensor. Certain characteristics of MODIS data have potential to complement high or moderate spatial resolution change detection requirements by offering solutions to some common limitations found with higher spatial resolution studies. For example, MODIS data continuity and synoptic spatial coverage of the globe reduce the problems associated with acquisition problems (e.g., Landsat failure) and wall-to-wall spatial coverage.

The method of analysis in this study focused on combining a Landsat segmentation (to produce the basic mapping features) and MODIS NDVI data to create a polygonal, mean NDVI layer of change for image differencing. Individually, each of these methods, i.e., the polygonal approach and image differencing methods are widely understood and employed in large-area mapping studies, however, few studies have combined the two approaches, specifically for a large-area habitat mapping application.

4.1.1 Map Update

The best mapping results reported in this thesis indicate that change in the Foothills Model Forest Grizzly Bear Research Program study area can be accurately detected with MODIS data with over 59% accuracy across the entire area. The comparable Landsat accuracy was over 80% correct (in comparison to manually-developed available GIS-based change maps). Although the overall map accuracy is lower with MODIS data than desired for many applications, this result does suggest that MODIS data are a suitable substitute when better data are not available. MODIS data worked particularly well when the area of the changed polygons exceeded about 15 hectares in size.

This map update result can be used to develop a list of steps for updating moderate resolution, large-area mapping initiatives specifically, the Foothills Model Forest Grizzly Bear Research Project. These steps assume that the land cover map exists and is in need of updating on an annual basis, and would include the following tasks:

I – IF Recent multi-date Landsat 5 TM/Landsat 7 ETM+ imagery is available:

1. Obtain Landsat 5 TM/Landsat 7 ETM+ imagery
2. Radiometric and geometric normalization (Chander & Markham, 2003)
3. Tasselled cap transformation (Crist & Cicone, 1984)
4. Enhanced Wetness Differencing Index (Franklin *et al.,* 2001)
5. Determine threshold of change (Franklin *et al.,* 2005)
6. Export to vector change layer
7. Assess accuracy compared to field or GIS data (expected to be over 80% correct)

II – IF Recent multi-date Landsat 5 TM/Landsat 7 ETM+ imagery NOT available:

1. Obtain industry/government land use vector file to delineate areas of anthropogenic change
2. Using existing imagery, manually digitize changes where visible
3. Obtain multi-date MODIS imagery for all areas of interest
4. Create polygon layer of mean NDVI values from the MODIS data, for example, using the VIMAGE algorithm from PCI Geomatica
5. Image differencing (T1-T2) where T2=most recent date

6. Image thresholding based on user knowledge and experimentation
7. Export polygons to vector change layer to 'fill in' where no change data exists
8. Assess accuracy compared to field or GIS data or TM data (expected to be over 59% correct)

The successful execution of these steps will provide a change layer that can be applied to the original segmented land cover map with or without actually changing the composition of the polygon-based map. In other words, the changes detected can be overlaid on the original map but not embedded in the land cover product, or a new land cover map can be generated with the changes 'burned' into the new map so that there are no distinctions between the original land cover mapping and the change updates – the best output product is, of course, dependent on the user needs against which the final product is to be measured.

Additionally, this study tested the sensitivity of the MODIS sensor to detect various sized-areas of change across large areas. Most studies that have used MODIS for detecting change typically focus on large areas of change (>5-10km^2) such as the large burned areas mapped by Fraser, *et al.* (2005) and Le Hegarat-Mascle, *et al.* (2005); specific scale limitations of MODIS-based updates have not yet been quantified. However, it has always been obvious that a 250m spatial resolution data set would not perform as well as a higher spatial detail image source (such as Landsat); the question might better be posed as 'what are the differences between maps updated with these different sources of information on environmental change?' Results in this thesis project show that the accuracy of the MODIS change detection increased with the size of the polygon. For example, changed areas >15 hectares in size were detected at accuracies of 79% or better in the test area using the MODIS data. This suggests that for certain applications, especially where detail is not as important, or in areas where it is known that only large-area changes have occurred, using the MODIS sensor may be an adequate choice of imagery.

4.1.2 Wildlife Habitat Application

To test the application of the MODIS-change map for wildlife studies, a comparison with the other change detection products in an actual wildlife habitat application was accomplished. A fragmentation analysis was performed using the concept of landscape metrics applied to the different change detection products; the widely-used FRAGSTATS program was used to calculate three landscape metrics that have already been shown to be of interest in the grizzly bear habitat work in the Foothills Model Forest (see Linke *et al.,* 2006): 1) edge density, 2) patch density and 3) Euclidean mean nearest neighbor (McGarigal *et al*., 2002). These landscape metrics can be used to model species richness, patch occupancy, and habitat quality over large areas. Additionally, this information is used not only to monitor the effect of current activities on species but to model and predict future scenarios (McGarigal *et al*., 2002; Linke *et al.,* In Review). For this study, three landscape metrics are calculated and compared for four map products:

1) The original GBRP Landcover Map (ORIGINAL),

2) The GBRP Landcover Map updated with the ΔGIS layer (ΔGIS Update),

3) The GBRP Landcover Map updated with the ΔTM layer (ΔTM Update), and

4) The GBRP Landcover Map updated with the ΔSM layer (ΔSM Update).

Comparing the three updated products with the original land cover map provides a good test of suitability and application of this method for wildlife management. The results are summarized in **Table 4.1**.

Table 4.1 Landscape Fragmentation Metrics

Layer	# of Patches	Patch Density	Largest Patch Index	Edge Density	Euclidean Mean Nearest Neighbor
ORIGINAL	23757	3.3487	22.6	61.38	306.4
ΔGIS Update	27298	3.8775	21.8	63.03	285.3
ΔTM Update	30989	4.402	21.2	63.18	272.0
ΔSM Update	30680	4.3579	20.5	64.18	271.7

The results of the landscape metric calculations suggest that the ΔSM Update (the MODIS polygon-based change update method) may be effective for use in these landscape metric calculations when compared to the same calculations based on the GIS data or based on the Landsat data. Generally, the differences between the resulting metrics are not large (as a proportion of the original land cover metric), and there are apparently reasonable ways in which the differences can be explained and understood.

For example, patch density expresses the number of patches within the entire reference unit on a per area basis (100ha) (Eiden *et al.,* 2006, McGarigal *et al.*, 2002). It is a good reflection of the extent to which the landscape is fragmented, and consequently, has been considered very useful in the assessment of landscape structure. Patch density enables comparisons of units with different sizes and therefore is particularly appropriate in the current map comparisons. Results of this metric calculation show that the differences between ΔSM and ΔTM are not very large (i.e., 4.3579 compared to 4.402); a more significant difference exists between ΔGIS (3.8775) and the other two update products. However, the ΔGIS metric is much more similar to the original land cover patch density.

This comparison of patch density suggests that for this metric, using the MODIS change detection technique may be comparable to that of the Landsat TM EDWI, but that both of these are quite dissimilar to that which would be calculated using the ΔGIS (if it were available). An interesting finding was that ΔTM actually resulted in the highest overall patch density, and the greatest difference when compared to the original land cover map. A possible explanation can be found within the other values included in **Table 4.1**. For example, ΔTM also shows the largest number of patches and the smallest patch size (Largest Patch Index) suggesting that the overall size of the changed areas and the polygons included significantly affects the results. This may be directly related to the fact that this product was able to detect smaller, more detailed changes such as well sites were not readily detected within ΔSM (Linke *et al.,* 2006). It has also been suggested in the literature that numerous, smaller features across a forest may have a higher impact on the overall landscape structure than fewer large disturbances; which is likely the case here (Saura, 2004; Linke *et al.,* In Review).

Edge metrics were also calculated for comparison. This metric quantifies patch boundaries by calculating and summing the perimeter of each patch, resulting in the total edge distance of each class and for the entire landscape (Saura, 2004). In contrast to patch density, edge density (m/ha) takes the shape and complexity of the patches into account which can be important for both "edge-loving species" and evaluating landscape heterogeneity (Eiden *et al.,* 2006). Within the study, the edge density calculation resulted in slightly different results compared to the patch density calculation. The interpretation of edge density would include the following trend: as the size of the patch increases, so does the edge density and thus, fragmentation. For this metric, ΔSM proved to result in the highest edge density, 64.18, however, this calculation again did not vary much between the three update products, ΔTM, 63.18 and ΔGIS, 63.03. But here again the ΔGIS map update resulted in a metric that was more similar to the original land cover map calculation.

Finally, the Euclidean nearest neighbor distance (ENN) was calculated for each of the map updates and the original land cover map. ENN is one of the simplest measures of patch context and has been used extensively to quantify patch isolation (Franklin, 2001). The ENN is calculated using simple Euclidean geometry as the shortest straight-line distance between the focal patch and its nearest neighbor of the same class (McGarigal *et al*., 2002). The overall trend of the results is similar to those of the previous two metrics calculated. ΔSM shows the lowest patch isolation again indicating the most fragmentation however, this value does not vary much from ΔTM, 272.0. As with earlier comparisons, there is a slightly higher difference when compared to the ΔGIS at 285.3. All of these are reduced values compared to the original land cover map – i.e., all of the change detection procedures show the appropriate change in magnitude of the metric, although there are differences in how much the original metric is affected when the update is provided by either the ΔGIS, ΔTM, or ΔSM methods. If these trends are understood, it is likely that the landscape metrics can be interpreted reasonably based on the changes that have been mapped with the different mapping technologies

Overall, I interpret that the results of the landscape metric calculations to suggest that the MODIS change detection (ΔSM) is an appropriate alternative in situations where higher spatial resolution data are not available or where pre-processing efforts are not possible or feasible. The differences between the three update products are evident – in both the maps and the calculation of landscape metrics – and it can be readily confirmed that 1) the coarser spatial resolution of the MODIS sensor is not appropriate for detecting finer details and 2) the polygon method creates some error of omission within the change class. However, overall the differences across the different landscape metrics are rather small (less than 10% in all cases) indicating that the MODIS polygon-based technique may be adequate for some landscape metrics and fragmentation studies. Further research into the effectiveness of the MODIS change detection and specific metrics is required.

This test also showed that there exists a significant difference in all three of the updated versions and the original version of the land cover map. The differences are always smaller (in proportion) when using the ΔGIS map. However, despite the loss of spatial detail when using coarser resolution spatial data (either the Landsat or the MODIS maps), the results of this study suggest that when no other data sources are available, the MODIS change update method may be more effective than not updating altogether. Ultimately, each mapping situation is case-dependent and depends on the user needs (i.e., maps are only useful if they can serve those who need them); thus, it is probably reasonable to conclude this brief test of map effectiveness with an emphasis on the fact that managers must carefully assess their spatial data needs and the requirements of each project or study independently.

4.2 Challenges and Limitations of this Research

Within the context of this research there are several obvious challenges, limitations and areas of future research. On the whole, coarse spatial resolution datasets, such as AVHRR and MODIS, are limited by low spatial detail and therefore, their applications are often restricted. For example, an analysis of burned areas in Canada using 1km AVHRR imagery by Fraser *et al.,* (2003; 2005) suggests that mapping accuracy degrades significantly for burns smaller than 1,000 hectares. Additionally, this thesis research found that changes smaller than approximately 15 hectares are not reliably detected by the MODIS sensor, and therefore, the map updates presented here are probably appropriate in some but possibly not other wildlife studies. For example, landscape fragmentation analysis may be reasonable when the landscape metrics are calculated using MODIS-based change detection maps although there are obvious differences when compared to mapped metrics calculated from TM-based or GIS-based change detection maps. More research on the impact of different mapping products on this landscape fragmentation and other wildlife applications may be useful in future.

Within the science of remote sensing, the results of all practical change detection studies are very dependent on change threshold selection (Franklin *et al.,* 2005); however, research on systematic threshold selection has been limited. This often requires the user to manually determine the level of change-no change, often with only limited knowledge in the field, and further demands previous knowledge of the study area which is not always available. This can limit the use of the final product significantly, especially in cases where no *a priori* data are available.

With all satellite data applications, and this thesis project is no exception, environmental and atmospheric effects pose a challenge that are known to affect the quality of the data and consequently the final maps that can be produced. The usual approach is to apply some form of radiometric normalization to some degree – and that was employed here, but no systematic accounting of the negative effects has been possible. For example, topographic effects have not been considered in this research, but are known to be pronounced in mountain areas (Franklin 2001). Recently, researchers have developed techniques that better account for some of these influences (Wulder *et al.*, 2003), however, it is also the case that these effects have an additional dimension when considered over two or more time periods (e.g., multi-date image differencing). Other influences are extremely difficult to eliminate, including haze and cloud cover, and these problems have the potential to negatively impact the integrity of data and the maps. More research on a few of these issues is suggested in the next section to enable greater success in remote sensing change detection.

The three main challenges encountered in this thesis research are associated with 1) threshold selection, 2) pixel size (or spatial resolution), and 3) pixel location (including segmentation or polygon-based updating of maps). Briefly, thresholding has long been an issue within satellite imagery change detection studies (Franklin *et al.,* 2005). The ability to select an appropriate threshold of change to exclude undesired 'noise' strongly determines the success of the change detection. Yet existing literature is not definitive in helping users decide on the best threshold, and available techniques are limited to essentially requiring the user to take a more qualitative approach, for example, based on aerial photo interpretation, field surveying and other *a* priori knowledge (Lyon *et al.,* 1998; Mas, 1999).

Pixel size and location are important mapping challenges when using different spatial resolution data sets. **Figures 4.1 and 4.2** show examples of this – when the pixel size is different in the update imagery, there can be new 'blockiness' introduced into the final update map product that may reduce user confidence and applicability. The pixel location problem suggests that the segmentation in the original land cover map may not be optimal for the update process – in other words, there can be a difference between the areas identified as change in the imagery and the available segments that need to be updated. Some decisions might be required that have little in the way of practical guidance to support them, and, again, user confidence and map applications may be compromised. Additionally, these figures display the challenges associated with polygon size and shape, again, a characteristic of the final map that is dependent on the original, segmented landcover product.

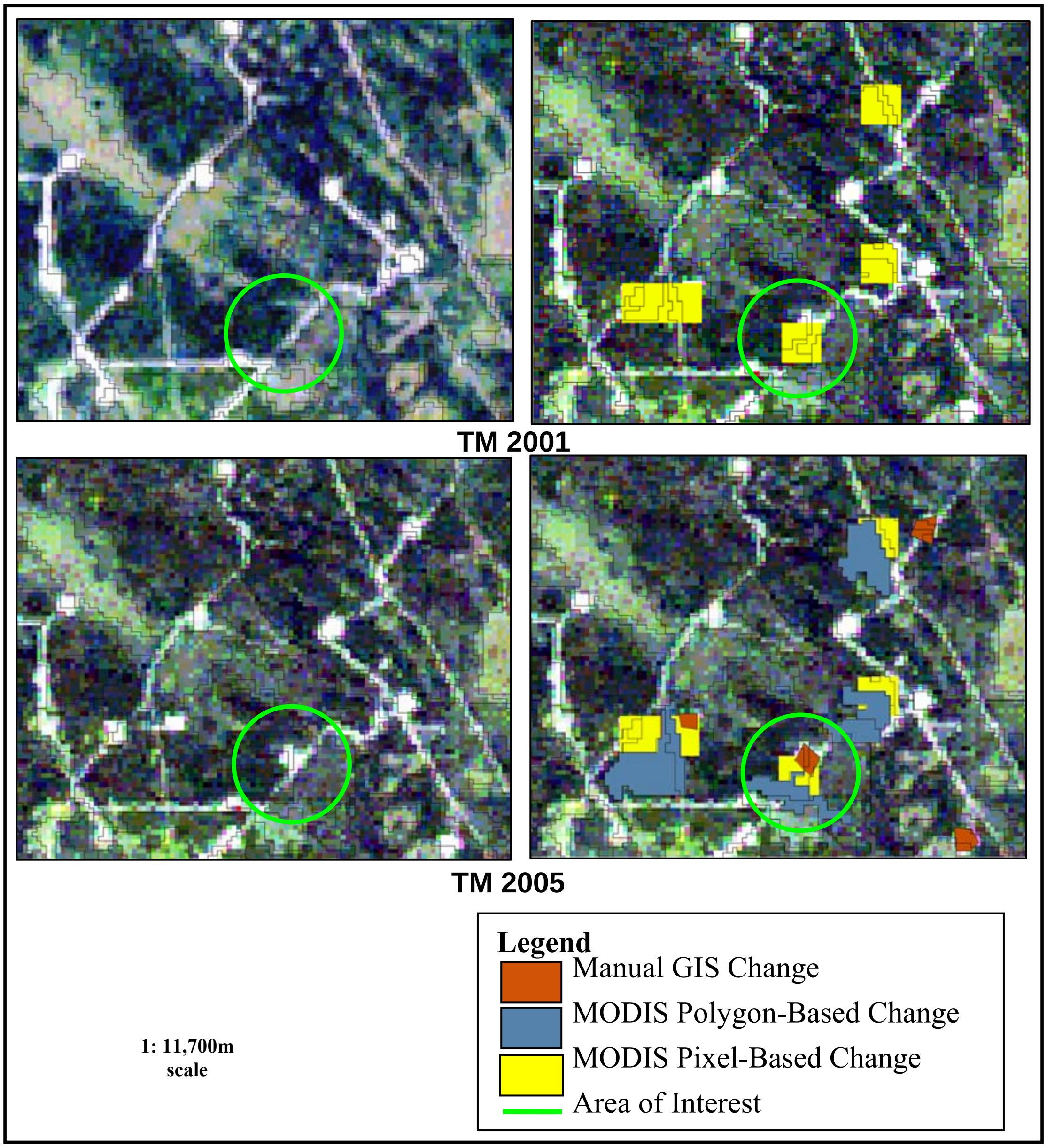

Figure 4.1: Examples of the limitations of pixel size and location. The green circle highlights one example of the effectiveness and the challenges of detecting wellsites using MODIS. The challenges are mainly associated with pixel location, pixel size, and polygon shape.

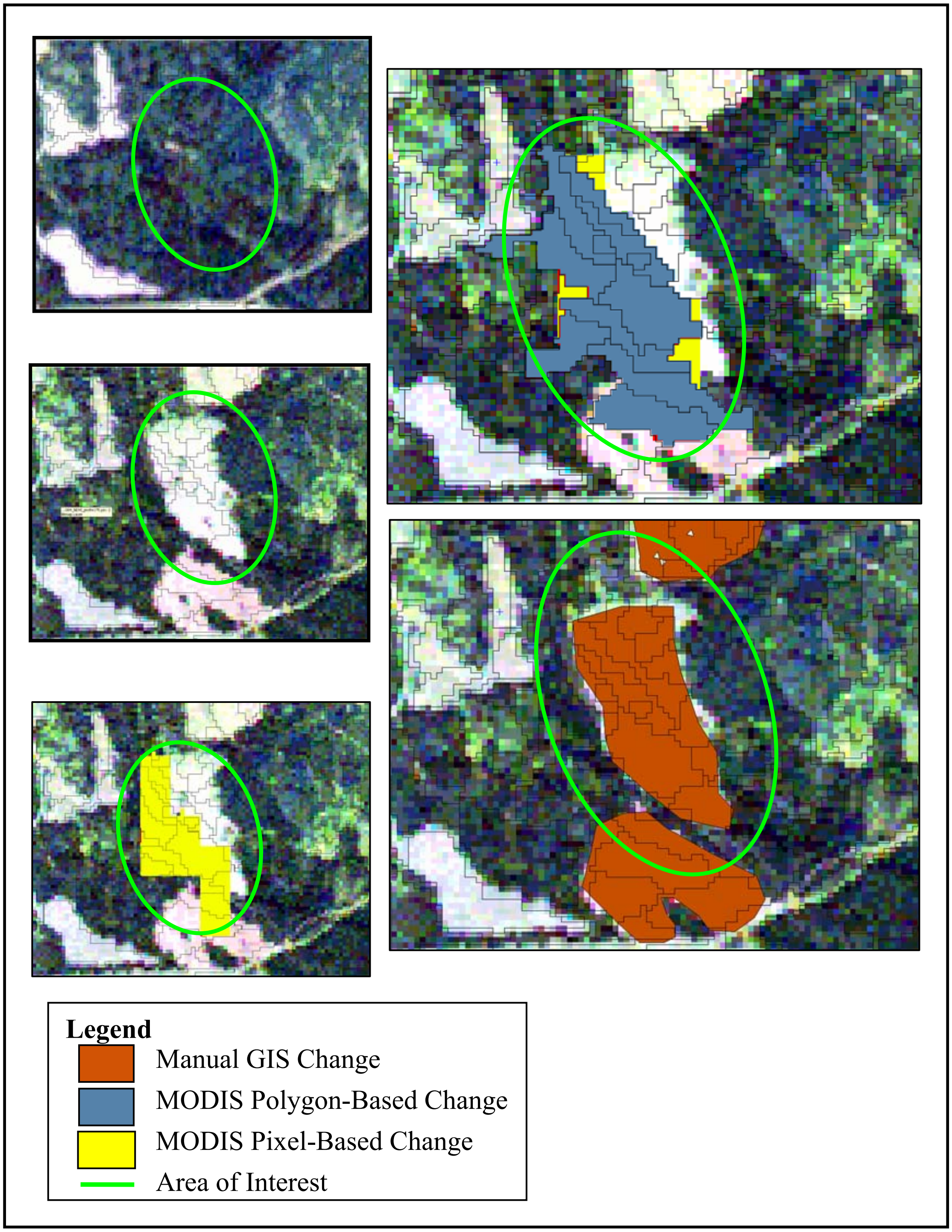

Figure 4.2: An example of the affect of pixel size and location on the detection of cutblocks.

4.3 Future Research

A number of key areas of future research are suggested based on the results and challenges presented in this thesis project:

- Coarse resolution imagery available from MODIS and AVHRR sensors may be very effective for large-area land cover mapping, however, a significant amount of detail and information is not present when these data are compared to Landsat or SPOT sensor data. This may create a mapping situation in which the data are suboptimal for change detection studies, but are clearly better than doing nothing and using an 'outdated' map. On the other hand, sensors such as MODIS offer a hyperspectral range of information available at a high radiometric resolution (11 bit or 2,046 shades of grey) which future research should investigate because of the increased information content of these data compared to only a few spectral bands tested in this thesis.

- Image differencing methods of change detection are widely popular but can be improved; also, more advanced methods have recently been suggested and could be the basis of additional research. One study by Fraser *et al.,* (2005) used a *series of change metrics* to detect forest cover change with 94% accuracy with similar data as was employed in this thesis research. The accuracy assessment method did vary significantly from the detailed GIS-based comparisons used in this study, for example, Fraser *et al.,* (2005) compared only that identified changes which were ‘permanent’ land cover changes; in essence, they were interested in multi-year results to aid in the ability to estimate carbon stock exchanges. They also identified that additional research is required in the area of change threshold determination. When implementing an image differencing technique, threshold selection is a crucial element in the success and accuracy of the final product as evident in the results of the present study, and those reported by Fraser *et al.,* (2005) and Franklin *et al*., (2005). To date, there is very limited literature available on this topic and the information that is available is generally concerned with simple pixel-based, high or moderate spatial resolution change detection data sets (Franklin *et al.,* 2005). Repeating similar studies with emerging coarser spatial resolution techniques previously mentioned may result in a systematic technique of deriving these threshold values. With an improved knowledge base on determining change thresholds, the results of the cumulative change detection ideas tested here may increase in accuracy.

- From the perspective of actual change detection research, further research into the radiometric normalization of MODIS datasets may improve the overall results of image differencing. A normalization pre-processing step is typically performed in finer resolution studies, for example, when using Landsat TM or ETM+, in an attempt to reduce the influence on the reflectance differences not attributed to actual landcover change. In the study by Fraser *et al.,* (2005), a Thiel-Sen regression applied to MODIS imagery proved to be effective in normalizing the broad-scale reflectance variations across Canada (their study area was the entire country). Additional studies that focus on this aspect will determine how to account for the error associated with radiometric, atmospheric and topographic differences; further work may be required in those areas of change that are the result of differences in phenology (seasonal vegetation models, for example).

- Much of remote sensing science is moving towards mapping methods that are comprised of more polygon-based methods; therefore, research into the various polygonal issues should be investigated, including the original land cover mapping specifications in the segmentation approach. More broadly, developing a rough guideline that provides information regarding optimal scale values for the derivation of specific land use or land cover features across the landscape may significantly improve the results of any mapping effort, and would have been of great value in this thesis project. The general idea is that change detection methods can be 'tailored' if there is a known relationship between the information content of the imagery and the type of changes that occur in the environment that is to be mapped; this would enable a more thorough multiple-scale approach to be implemented in which different parts of the mapping region are mapped for updates with different sources of data. Differences in using the pixel-based and polygon-based may prove different results and should be tested.

- And finally, as with most remotely sensed data, the methods applied in this thesis do not provide a replacement for actual ground data, or even the need for higher spatial resolution data; rather, the use of the MODIS-based methods suggests an alternative to heavy reliance on more traditional, field methods or when image availability or funding are limited. Better understanding of the sensitivity of MODIS to changes that occur in this area has been obtained, but additional work might be necessary in other areas to extrapolate these findings – for example, in primarily agricultural or different forest/wetland environments. Overall, however, it is expected that, by following the methods as outlined in this thesis for preliminary change detection over large areas in the Canadian Rocky Mountains, a more detailed mapping of the most significant change areas can be identified for further higher spatial resolution studies. It would also be useful in future to develop a more systematic examination of the effect of the different map update products on specific wildlife applications, including landscape fragmentation and habitat monitoring over large areas and long time periods.

4.4 References

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